# Conflict and its Impact on Education Accumulation and Enrollment in Colombia: What we can learn from recent IDPs*

Kate Wharton† and Ruth Uwaifo Oyelere‡

May 1, 2012

**Abstract**

*Forty years of low-intensity internal armed conflict makes Colombia home to over 3 million Internally Displaced Persons (IDPs), the world's largest population. The effect of violence on a child's education is of particular concern because of the critical role that education plays in increasing human capital and productivity. This paper explores the education accumulation and enrollment gaps created by being directly affected by conflict. First, we show that children living in high-conflict municipalities have only small gaps in education accumulation and enrollment in comparison to those living in low-conflict municipalities. These gaps grow when we compare those directly affected by conflict (IDPs) to non-migrants. Even when we compare IDPs to other migrant groups, the education gap persists. Our results suggest significant education accumulation and enrollment gaps for children of IDPs that widen to over half a year in secondary school. The difference that emerges we focus on direct exposure to conflict versus simply living in a high-conflict municipality suggests a need to distinguish between general and targeted violence when estimating the impact of conflict on education outcomes.*

**JEL classification:** I24, O12, O15, J10

**Keywords:** Education Attainment, School Enrollment, Colombia, Internal Displacement, Conflict

*Data for this paper was derived from IPUMS International. Comments are appreciated.

†kwharton3@gatech.edu, Georgia Institute of Technology

‡Corresponding author. ruth.uwaifo@econ.gatech.edu, School of Economics, Georgia Institute of Technology, 221 Bobby Dodd way, Atlanta, GA 30332

# 1 Introduction

For over forty years, Colombia has been troubled by armed conflict. The primary aggressor, the Revolutionary Armed Forces of Colombia (FARC), emerged as a revolutionary Marxist organization in the 1960s in response to political exclusion of the rural poor. Later, right-wing paramilitaries formed formed to counter the leftist FARC. Both irregular armed groups have since come to rely on narcotrafficking and other illegal activities to finance the conflict and are criticized internationally for human rights abuses targeting civilians.[1] Although peace talks have occurred under nearly every president, attempts at negotiation and disarmament have failed to bring lasting peace.

One result of this disruptive, long-term conflict is the mass displacement of Colombians. Currently, Colombia has the most internally displaced persons (IDPs) of any country in the world, with 3.6 million registered since 1997 according to the UNHCR 2010 Global Trends report. Empirical evidence suggests that IDPs move as a direct result of fighting, land confiscation, massacre, fear of forced recruitment into the armed groups, death threats, death of family or community members, and other fear-inducing elements of conflict (Kirchoff and Ibáñez 2002). After moving, IDPs face obstacles to social and economic integration in receptor locations, including psychological trauma, reduced social capital, family fragmentation, difficulty finding employment, and loss of assets. For example, Kirchhoff and Ibáñez (2002) show that 83% of landowners in their study were forced to abandon their land without compensation. The particular challenges of forced displacement suggest that IDPs are a highly vulnerable group requiring special attention in order to successfully integrate into the larger community.

Although efforts have been made to protect IDPs and to assist them in resettlement, there is anecdotal evidence that IDPs are still vulnerable many years after migration.[2] One possible explanation for this is that government aid to IDPs is restricted to the first three months of displacement. Meanwhile, longer-term income generation programs have had only limited success in helping IDP families return to their previous economic status (Ibáñez and Moya 2009).

Education significantly improves an individual's chances to increase welfare and escape poverty and plays a critical role in socioeconomic development. Our goal in this paper is to show how being directly affected by conflict impacts education outcomes of school aged children in Colombia. To do so, we answer four related questions.

First, are there education accumulation and enrollment gaps for children living in high-conflict

[1] It should be noted that the Colombian Army has also been criticized for 'false positive' killings of civilians.

[2] The 1997 Law 387 dictates government policy concerning assistance to IDPs and establishes the Network of Social Solidarity (RSS) as the coordinating entity for the strategic plan for the management of internal forced displacement. However, government programs reach only a small portion of the registered IDP population, and UN agencies and other humanitarian organizations play an important role in assisting the displaced.

municipalities compared to those living in low-conflict municipalities? Second, are there education accumulation and enrollment gaps for IDP children compared to non-migrants? Third, does living in a high-conflict municipality create a similar education gap as being directly affected by conflict? Finally, how do recent IDPs compare to other migrants in terms of education accumulation and enrollment?

We make use of the Colombia 2005 Census data and the Office for the Coordination of Humanitarian Affair's Humanitarian Situation Risk Index in this paper. To answer questions pertaining to education accumulation, we use linear regression models and fixed effect models, and for questions related to enrollment, we estimate probit models and compute marginal effects.

To answer the first question, whether living in a high-conflict municipality creates an education gap, we use a dummy variable, setting as one those who live in high-conflict regions. We identify individuals who fall into this category as those living in municipalities with conflict greater than the mean. Controlling for factors that predict school accumulation and enrollment, and separating children 6-11 years old from those 12-17 years old, we estimate the gap between individuals in high-conflict municipalities and those living in all other municipalities. We find a slight gap in accumulation of about 0.04 years and a gap in probability of enrollment of about 1% across both age groups. However, if we cluster at the municipality level, most of these estimated impacts become insignificant.

Second, we ask if an education gap exists between IDP and non-migrant children. We first divide the sample of subgroups consisting of several types of migrants linked with their reason for moving, and a base group of non-migrants. We focus on recent IDPs because we have no way to identify IDPs who migrated more than five years ago.[3] Using both the education accumulation and enrollment models, and controlling for important factors that predict school-related outcomes, we find a large and statistically significant education gap. IDP children ages 6-11 have about 0.2 years less schooling than non-migrants, holding all else equal, while children ages 11-17 have an even larger gap of about 0.5 years. With respect to enrollment, we find that IDP children ages 6-11 and 12-17 are 1.6% and 6.3% less likely to be enrolled in school than non-migrants, respectively.

To compare the education gaps created by living in a high-conflict municipality and by being displaced by conflict, we restrict our sample to only those living in high-conflict municipalities. Assuming that IDPs found in these regions are not a select group and that living in a conflict region creates similar effects as being directly affected by conflict, there should be no accumulation or enrollment gap between IDP children and all other children living in a high-conflict municipality.

[3]From now on, we will refer to recent IDPs simply as IDPs. We also refer to those who are directly affected by conflict as IDPs.

We estimate the education accumulation and enrollment models on this sub-sample and find that a gap still exists and in fact grows. Specifically, we find that for IDP children ages 6-11 and 12-17, the education accumulation gaps range from 0.22-0.32and 0.56-0.61fewer years of schooling than non-migrant children, depending on the level of conflict to which the sample is restricted. With respect to enrollment, evidence is mixed. For the 6-11 years age cohort, there does not appear to be an enrollment gap. However, at the secondary level, children of IDPs in high-conflict regions are approximately 11%less likely than non-migrants to be enrolled in school. These estimated education gaps in high-conflict municipalities largely mirror the gaps we see when considering all municipalities, particularly with regard to education accumulation, where we see magnitude of the gap grow in higher-conflict municipalities.

The possible argument that non-migrants are not a good comparison group for IDPs leads to our last question. To compare IDPs with other migrant groups in terms of education, we estimate the accumulation and enrollment models, limiting the sample to only migrants.[4] We restrict our sample first to recent migrants because we can only detect recent IDPs in our data. However, as a robustness check, we also expand the sample to anyone who has migrated from their place of birth. We find that the accumulation and enrollment gaps persist and are only slightly smaller than when we compare IDPs to non-migrants. For children ages 6-11, there is less evidence of an education gap when we restrict the sample to recent migrants. The accumulation gap for children ages 12-17 shrinks from 0.51 years when IDPs are compared to non-migrants to 0.34years in comparison to other migrants.

We conduct robustness checks on our main results using a fixed effect model and matching estimators, and our inferences are still the same. The findings from our analysis suggest that all other things being equal, though living in a high-conflict area may affect a child's education accumulation and enrollment, the impact is far less than being directly affected by conflict. In addition, we find that these effects are larger at the secondary level.

This paper contributes to the literature by highlighting the direct impact of conflict on education accumulation and enrollment in Colombia. While past literature looks at the impact of conflict on education outcomes, it generally investigates differences before and after a short, high-intensity civil war or focuses on the impact of living in a high-conflict area. In cases of short, intense fighting, this approach may be appropriate, but we find that in the face of the low-intensity, protracted conflict in Colombia, a different approach is needed. Looking at individuals who have been directly affected

[4] The literature shows that migrants are a select group who on average tend to fall behind in education accumulation and enrollment. However, IDPs cannot be considered a select group of voluntary migrants because their migration is linked to exogenous events.

by conflict provides greater insight on the impact of conflict on education outcomes. To the best of our knowledge, we are the first to focus on estimating the education accumulation and enrollment gaps for children displaced by conflict in Colombia.

The rest of the paper proceeds as follows. In section two, we review the literature on conflict and education and also highlight studies of IDPs in Colombia. Section three is a summary of our data sets. In section four, we provide a descriptive analysis of the data. Section five shows our empirical model, and section six provides a detailed summary of our finding and robustness checks. We conclude in section seven.

## 2 Literature Review

Education outcomes and the factors that affect these outcomes are considered extensively in the literature. Specifically for Colombia, one factor considered is the opportunity to attend private school through a voucher program. Angrist et al (2002) examine the short term effects of the use of vouchers on students who applied for the vouchers in Bogotá in 1995. The longer term effects of this program are also considered by Angrist et al (2006). They find that the voucher program increased secondary school completion rates by 15-20%. Returns to education in Colombia have also been estimated by several authors[5]

Factors that affect school attainment and enrollment have been analyzed both within and outside Colombia. Migration, income shocks, loss of life, and institutional quality are examples of factors examined in the literature.[6] Another factor that affects attainment and enrollment highlighted in the more recent literature is conflict. However, the challenges of collecting accurate household level data during armed conflict volume of studies on this topic.

In one of the few studies to assess the impact of conflict on education attainment using microeconomic data, Shemyakina (2011) studies the impact of the 1992-1998 civil conflict in Tajikistan on school attainment and enrollment. Shemyakina finds that regional-level exposure to the Tajik civil conflict had little or no effect on boys' enrollment. However, it had a large negative effect on girls' school enrollment. Akresh and de Walque (2008) study the effects of the 1994 Rwandan genocide on schooling. The authors find that children who lived through the Rwandan genocide, concentrated

[5] See Poveda and Sossa (2006), Gaston and Tenjo (1992), Psacharopoulos and Velez (1992,1993) and Psacharopoulos (1994).

[6] See McKenzie and Rapoport (2010) for the impact of economic migration on education attainment in rural Mexico, Evans and Miguel (2007) for the effect of losing a parent and the importance of institutions, and Glewwe and Jacoby (1994) for the impact of availability and quality of school facilities on education attainment in Ghana. Also see Jacoby and Skoufias (1997), Duryea et al (2001), and Thomas et al (2004) for the impact of income shocks on schooling decisions in peaceful environments.

during a 100-day period, lost nearly a half year of schooling compared to their peers who were not exposed. They were also 15% less likely to complete grades three and four. For Guatemala, Chamarbagwala and Morán (2011) examine the impact of exposure to the 36-year civil war on education outcomes for the rural Mayan population. Exposure is measured as a department-level variable indicating number of human rights violations and acts of violence. In this disadvantaged group, the authors find a strong negative impact of conflict on education accumulation. For the three periods of the civil war identified, rural Mayan males showed a 0.27, 0.71, and 1.09 year decline in education attainment, while females showed a 0.12, 0.47, and 1.17 year decline. With very low education attainment overall, this amounts to a 23% and 30% decline in years of schooling during the third period of the war for males and females, respectively. Taken together, the literature on Tajikistan, Rwanda, and Guatemala suggests that exposure to conflict negatively affects education outcomes. However, each of these studies looks at regional-level exposure to violence during a high-intensity conflict. Compared to the conflicts in Tajikistan, Rwanda, and Guatemala, the conflict in Colombia is much more protracted, low-intensity, and involves a greater number of irregular actors. These actors employ strategies that directly target civilians for expulsion, recruitment, and assassination. In this situation, we cannot assume that every individual in a high-conflict region is equally exposed to violence.

Several authors investigate the relationship between violence and education in Colombia. Barrera and Ibáñez (2004) develop a theoretical framework to explore the three ways in which violence can affect education. First, violence directly reduces the utility of individuals. Second, it destroys physical capital, creating uncertainty, deterring investment, and reducing productivity. Third, it reduces returns to education because education is not viewed as a value-enhancing commodity.[7] The authors also show a statistically significant gap in school enrollment rates between municipalities above and below the median national homicide rate. They find that violence has a negative impact on school enrollment at all ages, and that this effect is particularly large for young adults. While the paper shows the negative effects of living in a violent municipality on school enrollment, it does not provide evidence on the impact of armed conflict on education outcomes of those directly affected by violence–the IDPs. It also does not discriminate between generalized violence and violence occurring as a direct result of the armed conflict. Dueñas and Sanchez (2007) go a step further by looking specifically at the impact of armed conflict. The authors look at the impact of conflict on another school related outcome, drop-out rates. Focusing on households in the eastern part of Colombia, they show using a duration model that the presence of illegal armed groups increases dropout rates, with increased effects for the poorest households. Though this paper considers the impact of the

[7] These channels through which armed conflict affects schooling are confirmed by Shemyakina (2011).

presence of armed conflict in an area on an education outcome, it does not look directly at IDPs, which we feel is important given the nature of the conflict in Colombia. Rodriguez and Sanchez (2009) build on Dueñas and Sanchez (2007) by considering the joint decision to drop out of school and enter the labor market. The authors suggest that conflict-related violence does not seem to affect education investments or child labor decisions for younger children, but it does negatively impact children over age 12. Also, the authors find that the effect of violence varies primarily with age rather than with gender or household wealth. Although looking at the impact of regional-level exposure to violence on education outcomes is useful, it may not reveal the full impact of conflict on those directly affected especially when the conflict is low intensity, less random and more targeted.

Though past research does not focus on the education gap of IDPs in Colombia, the plight of the displaced in general has been considered. First, Kirchoff and Ibáñez (2002) study the probability of individual or household migration in Colombia and find that households that have been directly affected by violence–either assassination or death threats–have a higher probability of migrating. Of the IDPs interviewed, 58.2% reported that a household member received a death threat, compared to only 9.1% of non-displaced from the high-conflict regions. The authors provide extensive descriptive data on the IDP population gained from interviews in three urban centers. Results indicate that "security considerations are not the only determinants of the displacement decision." Rather, displacement may be motivated by individual characteristics, such as risk aversion, or external factors such as direct targeting by guerrilla and paramilitary groups. Ibáñez and Moya (2006, 2009) look at the vulnerability of IDPs over time and find that because IDPs are unable to successfully integrate into the urban economy, well-being decreases and households are forced to take drastic measures in order to smooth consumption. Lozano-Gracia et al (2010) find that while the majority of IDPs migrate to geographically proximate locations, individuals from municipalities in the top 10% of violence levels will move far from their municipality of origin, perhaps in hope of distancing themselves from the conflict. Taken together, the literature on IDPs in Colombia suggests vulnerability stemming from loss of assets, potential psychological effects of fear and targeting, and loss of income, all of which we expect to influence education outcomes.

Given that the effect of conflict-induced displacement on human capital investment in children is important but largely unexplored, this paper will investigate the enrollment and attainment gaps between IDP children, other migrants, and non-migrants.

## 3 Data

The data we use to answer our questions of interest comes from two sources: the Colombia 2005 Census and the the Office for the Coordination of Humanitarian Affairs. We accessed the 2005 Census via IPUMS-International,[8] and the majority of the data we use comes from this source. This data includes over two million observations, a 5% sample of the 2005 Colombian Census, which is notable for its accuracy and coverage.

We are able to identify IDPs from this data using those who state that they migrated in the past five years and select "violence or insecurity" as the reason for migrating. This technique of identifying IDPs has two potential limitations. First, we are unable to identify IDPs who moved more than five years ago. This is because though we can identify indirectly all who have migrated by comparing birth place to current place of residence, the question that allows us to identify IDPs is restricted to those who migrated in the last five years. This limitation implies that we are unable to look at the long term enrollment and attainment effects of direct exposure to conflict. Second, the responses to the question of why you migrated are mutually exclusive, so each person selects only one motivation for migration. This could potentially be an issue if an individual migrated for more than one reason. However, we find this restriction advantageous because it forces people to pick their most important reason for migrating. This allows us to isolate the individuals most directly affected by conflict. Still, about 0.32% of the sample of recent migrants do not report reason for migration, so this group may include IDPs who felt uncomfortable reporting their reason for migrating. We create a separate category for these observations, but given the small sample size, we do not worry about the potential impact of these observations.[9] The census data is appropriate for this analysis not only because it has a large sample and allows us identify IDPs, but also because it has a wide range of variables that we use as controls in our enrollment and accumulation models. The major limitation of the data is the lack of information on income. However, the Colombian census has many indicators for poverty and wealth which we use as proxies for income.

The source of data concerning humanitarian risk, conflict, capacity, social, and economic levels per municipality is the Humanitarian Situation Risk Index (HSRI), calculated by the Office for the Coordination of Humanitarian Assistance in collaboration with the Universidad Santo Tomas in 2008. The HSRI was developed with the purpose of calculating the probability that a humanitarian situation will occur at the municipality level in Colombia. Four sub-indices of risk are calculated and

[8]Minnesota Population Center. Integrated Public Use Microdata Series, International: Version 6.0 [Machine-readable database]. Minneapolis: University of Minnesota, 2010.

[9]We do not suggest that our method identifies all those who officially registered with the government or international organizations as IDPs during our data period. However, we are confident that we capture most of those whose move was primarily driven by direct exposure to conflict from 2000-2005.

used to determine the overall humanitarian risk: conflict, response capacity, social, and economic. Sources of HSRI data are included in Appendix 1. A HSRI value and a value for each of the risk indicators is provided for each of 1,100 Colombian municipalities. However, only 532 municipalities or groups of municipalities are defined in the 2005 Census because in many cases small municipalities are grouped together. We can see which municipalities are included in each grouping, but we cannot further divide the data. In order to incorporate the HSRI and its sub-indices data into the 2005 census data, we assign to each individual the value of each index in their current municipality. In some cases where small municipalities are grouped together in the census, we find the average HSRI and other sub-index values for all of the municipalities in that particular grouping.

## 4 Descriptives

In this section we present some descriptive statistics to further motivate our discussion on the education attainment and enrollment of IDPs.[10]

Table 1 presents summary statistics of basic indicators for IDPs in comparison to other migrants. Notice that in comparison to other migrants, IDPs are older, more likely to be male, have more children in the family, less likely to be married, less likely to be in an urban area, more likely to be black or indigenous, less likely to be literate, less likely to be employed, and more likely to be disabled. Compared to non-migrants, IDPs are younger and have fewer years of schooling, and there is less of a difference with respect to being married, gender, living in an urban area, employment, and race. This may be because other migrants represent a select group. Notice that IDPs differ significantly in some variables that may be indicative of experiences characteristic of those who have been directly affected by conflict. For instance, IDPs are more likely than any other group to be disabled, and they have the lowest likelihood of owning a dwelling. With respect to education accumulation, Table 1 shows that IDPs have a lower mean education attainment than non-migrants and other migrants. IDPs also have more children than other groups despite having similar probability of being married and similar mean age. This difference may suggest that families with children are more likely to be directly affected by conflict than those without or that families with children are more likely to migrate if directly affected by conflict. The summary in Table 1 confirms the existing literature that IDPs are vulnerable. Although the literature suggests that migrants are a select set with exceptional drive, the findings below suggest that IDPs do not fit the mould of other migrants on average.

[10]It should be noted that through out this study, "IDPs" refers to Colombians who have migrated because of conflict, according to the 2005 census. Natural disaster migrants are treated as a separate category.

Table 1: 2005 Census: Descriptive Statistics

| Category | IDPs | Other Migrants | Non-Migrants | All |
|---|---|---|---|---|
| Age | 27.059 | 26.691 | 29.060 | 28.586 |
| Male | 0.509 | 0.492 | 0.503 | 0.501 |
| No. children | 0.984 | 0.787 | 0.809 | 0.807 |
| Married | 0.370 | 0.401 | 0.354 | 0.363 |
| Urban | 0.523 | 0.702 | 0.553 | 0.581 |
| Race: White | 0.705 | 0.836 | 0.796 | 0.803 |
| Race: Black | 0.170 | 0.110 | 0.103 | 0.105 |
| Race: indigenous | 0.072 | 0.030 | 0.071 | 0.063 |
| Yrs school | 4.354 | 6.321 | 5.125 | 5.349 |
| Literacy | 0.738 | 0.823 | 0.739 | 0.755 |
| Employed | 0.307 | 0.366 | 0.273 | 0.291 |
| Disabled | 0.082 | 0.058 | 0.073 | 0.070 |

To further motivate our discussion, we present some enrollment statistics. Table 2 shows proportion enrolled in school by age cohort and migration status. These summary statistics suggest that the displaced are less likely to be enrolled in school than any other group in all school age categories. The enrollment gap is particularly substantial over age 12. We do not infer from these summary statistics that being displaced created these enrollment differences. It is possible that the displaced come from municipalities with less access to quality education facilities or move to communities with less access which may lead to lower probability of enrollment.

Table 2: 2005 Census: Proportion Enrolled in School

| Age Cohort | IDPs | Other Migrants | Non-Migrants | All |
|---|---|---|---|---|
| 6-11 | 0.830 | 0.901 | 0.891 | 0.892 |
| 12-17 | 0.645 | 0.724 | 0.735 | 0.732 |
| 18-21 | 0.253 | 0.281 | 0.278 | 0.278 |
| 22-25 | 0.097 | 0.149 | 0.135 | 0.138 |

In Table 3, we compare IDPs with other vulnerable groups to highlight the fact that though our discussion is focused on IDPs, IDPs are not the only vulnerable group in terms of education. The other vulnerable groups we isolate are those who migrated because of natural disaster, the disabled, and the poor.[11] At the level of primary education, ages 6-11, the displaced are more likely to be

[11] We identify the poor in Table 3 through the wall materials of their housing.

enrolled than any of these other vulnerable groups, with 83% enrollment. The displaced, natural disaster migrants, and the disabled have similar enrollment rates from ages 12-21. Not surprising, at all ages, the very poor lag behind in terms of enrollment, suggesting the need to control for income or socioeconomic level in our regression analysis.

Table 3: 2005 Census: Enrollment Statistics for Vulnerable Groups

| Age Cohort | Migrated: Displaced | Migrated: Natural Disaster | Disabled | Poor living conditions |
|---|---|---|---|---|
| 6-11 | 0.830 | 0.814 | 0.792 | 0.779 |
| 12-17 | 0.645 | 0.630 | 0.632 | 0.589 |
| 18-21 | 0.253 | 0.233 | 0.236 | 0.162 |
| 22-25 | 0.097 | 0.114 | 0.114 | 0.065 |

Table 4 highlights the education attainment of the displaced, other migrants, and non-migrants. Table 4 indicates that IDPs have much lower attainment than any of the other groups, and that the gap grows over time. These results can also be seen graphically in Figure 1. The gap grows significantly in the 12-17 age cohort, with the displaced achieving approximately 1.05 fewer years of schooling than non-displaced migrants and 0.92 fewer years than non-migrants. The large difference between this group and other migrants is likely attributable to the large proportion of other migrants who have moved for study and are therefore reach very high education attainment.

Table 4: 2005 Census: Education Attainment

| Age Cohort | Displaced | Other Migrants | Non-Migrants | All |
|---|---|---|---|---|
| 6-11 | 1.948 | 2.188 | 2.317 | 2.287 |
| 12-17 | 5.484 | 6.535 | 6.408 | 6.419 |
| 18-21 | 6.868 | 8.692 | 7.992 | 8.132 |
| 22-25 | 6.732 | 9.064 | 7.992 | 8.253 |

The highlighted descriptive statistics all suggests that IDPs are vulnerable in terms of education. Even if we focus solely on potentially vulnerable migrants (migrants who have moved because of natural disaster, health, or displacement) as in Figure 2, we still see that IDPs end up with fewer years of schooling. Notice that IDPs migrants appear to achieve similar years of schooling as other vulnerable migrants until secondary school, when health migrants move ahead and the displaced fall behind. By age 17, the gap has widened even more, with the displaced achieving approximately 3

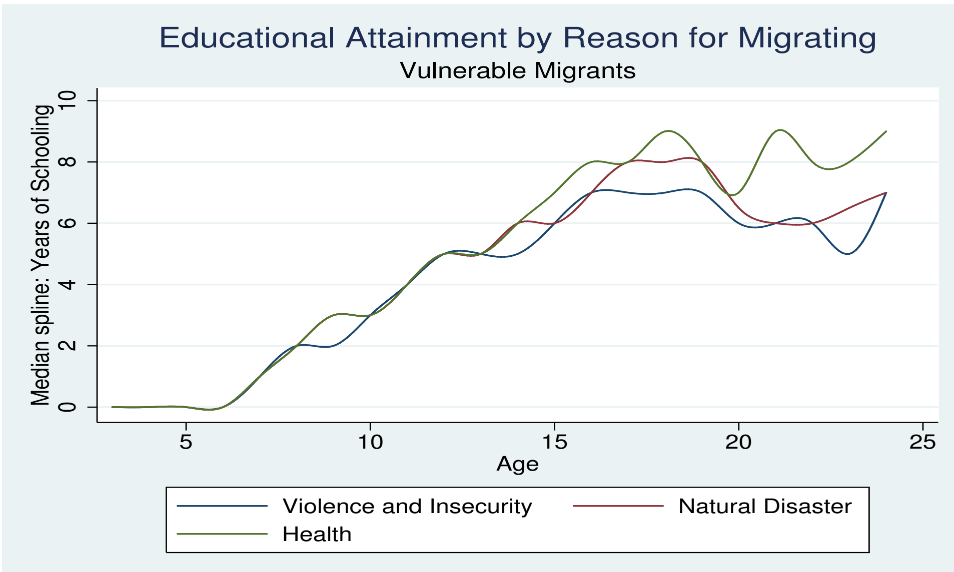


Figure 1:

years less schooling than those who migrated for health reasons, and natural disaster victims falling somewhere in between.

One of the points we make in this paper is that IDPs are not like most other migrants, particularly compared to those who migrated for endogenous rather than exogenous factors. Figure 3 highlights the school attainment trend for three group of voluntary migrants: those who migrated for work, family, and study. The results are logically consistent; study migrants achieve the greatest years of schooling, and work migrants achieve the fewest. It should be noted that again, the gap does not emerge until secondary education. All of the non-vulnerable groups shown in Figure 2 achieve higher median education attainment than the displaced population.

These preliminary descriptive statistics suggest that children of IDPs are vulnerable with regard to education. In this paper, we focus on the education accumulation and enrollment impact of direct exposure to conflict on children. Even though the above results suggest lower mean education accumulation and enrollment for IDPs or their children, this result does not imply that conflict is responsible for the gap. It is possible that children of IDPs have parents with lower education or who are poorer. In this scenario, a gap in education attainment or enrollment is expected. To evaluate the possible effect of direct exposure to conflict, we turn to econometric analysis.

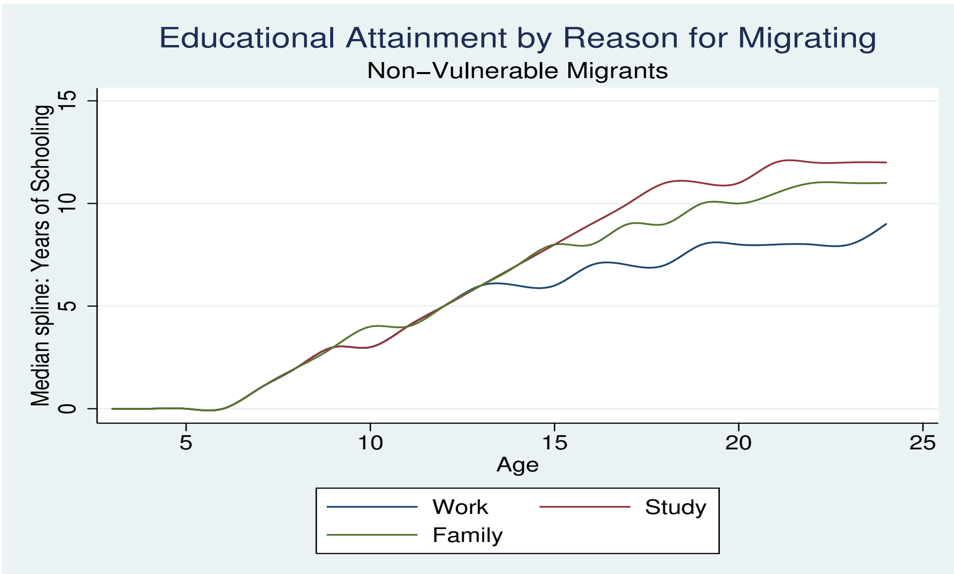


Figure 2:

## 5 Empirical Strategy

As mentioned above, we focus on four main questions in this paper. First, is there an education enrollment and accumulation gap for children of those living in municipalities with high conflict in comparison to those living elsewhere? Second, is there an education accumulation and enrollment gap for children of those directly affected by conflict? Third, does living in a high-conflict municipality create similar education accumulation and enrollment gaps as being directly affected by conflict? Finally, how do IDPs compare to other migrants in education accumulation and enrollment? Our underlining goal in answering these four questions is to provide overwhelming evidence that direct exposure to conflict leads to an education gap.

To answer our first question, we estimate a school accumulation empirical model (equation (1)) and a school enrollment empirical model (equation (2)) for a typical individual.

$$y_{ic} = \alpha_c + X_{ic}'\gamma_c + F_{ic}'\delta_c + R_{ic}\beta_c + W_{ic}'\theta_c + \epsilon_{ic}, \;\; i = 1, ....., N \tag{1}$$

We assume the the regression error $\epsilon_i$ is uncorrelated with the regressors. Here, y is years of schooling for individual i in a particular age cohort c. We focus on two cohorts in our analysis, ages 6-11 and ages 12-17, because these age groups corresponds with Colombia's school system - primary and secondary school. X is a vector of variables that affect a child's schooling. These variables include gender, economic status correlates, family size, mother's years of schooling, father's years of schooling, number of children of mother, class of work of father, class of work of mother, and employment status of father. F is a vector of dummy variables that are important to control for, such as state of residence and race. R is a dummy variable that takes a value of 1 if a child is in a high-conflict municipality and 0 otherwise. The vector W consists of regional controls such as if an area is urban or rural and the social capacity and level of conflict of a municipality. $\epsilon$ is the error term. The inclusion of parent-related variables reduces the potential of omitted variable bias given the importance of parents' education as a predictor of child's education. However, including these variables comes at a cost because not all children in the sample have information about parents. We drop all children who do not have information on both parents' education from the sample we estimate. However, later in the paper we address of whether using the restricted sample for which parental information is available creates a biased estimate.

To answer the second part of question 1, we assume that a child being enrolled in school is a function of a set of variables Z. In this case, our independent variable is a binary variable that takes a 1 when a child in a particular age cohort is enrolled and 0 otherwise. We rewrite equation (2) assuming a probit modeling strategy. The $\Phi$ in equation (3) our empirical school enrollment model indicates that this is the Cumulative Distribution Function (CDF) of the standard normal distribution. The description of the variables is the same as in equation (1) above. Using a probit model, we estimate equation (3) and find the marginal effects. The marginal effects represent the impact of a unit change in each independent continuous variable on the probability of being enrolled in school. This provides a straight forward interpretation of estimated results from the probit model. For dummy variables like R, which is the focus of the first question, the interpretation of marginal effects is slightly different. The marginal estimate captures the difference in the probability of being enrolled in school for a particular group dummy relative to the baseline group. In the case of R, the estimated marginal effect captures the probability of being enrolled in school for a certain age cohort living in a high conflict municipality relative to those living elsewhere.

$$Prob(S = 1|Z) = F(Z'\beta) \tag{2}$$

$$Prob(S_{ic} = 1) = \Phi(\alpha_c + X'_{ic}\zeta_c + F'_{ic}\xi_c + R_{ic}\lambda_c + W'_{ic}\phi_c) \;\; i = 1, ....., N \tag{3}$$

For the second question, our empirical strategy is to first estimate equation (4) using OLS. Notice equation (4) is very similar to equation (1). The difference lies in the matrix M in equation (4) replacing dummy variable R. To answer the second part of question two, we also alter our enrollment empirical model, equation (3), dropping R and including M in equation (5). Once again we compute and report marginal effects for the enrollment model.

$$y_{ic} = \alpha_c + X'_{ic}\gamma_c + F'_{ic}\delta_c + M'_{ic}\beta_c + W'_{ic}\theta_c + \varepsilon_{ic}, \;\; i = 1, ....., N \tag{4}$$

M is a vector of dummy variables that divides the population based on cause for migration in the last five years. For these dummy variables, the base group is people who have not moved in the last five years. We call this group non-migrants. Among the migrant cause dummies, we have a dummy for those who migrated because of violence or insecurity. This is our identifier of IDPs and the dummy we will focus on in answering the question of whether there is an education gap for IDPs.

$$Prob(S_{ic} = 1) = \Phi(\alpha_c + X'_{ic}\zeta_c + F'_{ic}\xi_c + M'_{ic}\lambda_c + W'_{ic}\phi_c) \;\; i = 1, ....., N \tag{5}$$

To address the third question, we re-estimate equations (4) and (5) on the sample of those exposed to conflict. To test the sensitivity of our result, we try different ways of defining the population exposed to conflict. First, we consider states with a conflict index above the mean. Next, we consider municipalities with conflict index above the mean. Lastly, we consider municipalities with very high conflict (in the top quartile of the conflict index).

We address the last question by again altering equations (1) and (3). In contrast to the first two questions for which we focus on both migrants and non-migrants, here we restrict our sample to only migrants. In addition, we alter the dummy variable R. Recall that for the first question, R=1 if a person lives in a municipality with high conflict. For this question, R takes the value of 1 if a person is an IDP and 0 if the person is a migrant for any other reason.

### 5.1 Potential econometric issues with estimating the impact of conflict

Given our focus on estimating the school accumulation and school enrollment gaps linked with conflict, it is important to highlight some basic issues that could make deriving consistent estimates of these gaps difficult. First, IDPs are migrants, and in general, analysis focused on migrants could be plagued with issues of selectivity. Migrants are a select group of people, and usually, looking at migrants' outcomes or the impact of migration on certain outcomes without controlling for selection could lead to biased estimates. However, IDPs are a unique group of migrants in that their migration is motivated by being directly affected by conflict. We can think of IDPs as involuntary migrants linked to exogenous forces. In contrast, migrants who moved for study, family reasons or work can be viewed as voluntary migrants linked to endogenous factors. Kirchhoff and Ibáñez (2002) note that not everyone in regions of high conflict migrates. Those who do leave have usually been directly affected in a significant way by the conflict, having lost family or property or received threats of such. The authors, show that 58.2% of IDPs surveyed received a death threat before migrating. In contrast, only 9.1% of those who did not migrate living in the same high conflict region that the IDPs migrated from had received a death threat. Given the uniqueness of IDPs' experiences and the largely exogenous nature of being directly affected by conflict, it may be possible to look at IDPs as a different kind of migrants that may not suffer from the selection bias plaguing other migrants. Assuming this is true, a regression in which we control for the factors that typically predict school attainment, the estimate of the gap in school attainment or enrollment between the IDP's and non-migrants can give us an approximate estimate of the impact of being directly affected by conflict. If however, non-migrants on average look very different from IDPs, then the estimated education accumulation or enrollment gap could be upward biased.[12]

Another variable that several authors have noted to be endogenous when included in an accumulation or enrollment model estimation is conflict. Conflict could be correlated with individuals being poor or living in an area with low levels of social capacity. Because both of these factors are important for human capital investment and school enrollment, the estimated effect of conflict could be inconsistent and over estimate the impact of conflict if we do not control for capacity or address the potential endogeneity in the conflict variable. Although the level of conflict in a region is merely a control rather than our major variable of interest for our second and third question, conflict in a region is used to define the exposure to conflict dummy for our first question and is also relevant for our last question. We try to avoid the potential bias in estimating the impact of exposure to conflict by controlling for the capacity in a municipality and also by including several poverty correlates and wealth indicators.[13] It is also important to mention that Rodriguez and Sanchez (2009) highlight another potential channel of omitted variable bias in estimating the impact of conflict on dropout rate.[14] They suggest that although exposure to conflict affects school enrollment, pressure to drop out of school also affects dropout rates and is correlated with conflict. Therefore, it is possible to

[12]We are of the opinion that we can make this assumption because we compared summary statistics for variables like age, family size, marital status and gender for IDPs, migrants and non-migrants. We noted only slight differences between IDPs and non-migrants but bigger differences between non-migrants and migrants. We do not compare summary statistics for variables related to education, employment or location (urban vs rural) as we expect that these variables will be affected by being exposed to conflict and so should differ across IDPs and non-migrants. The only variable we note significant difference between IDPs and non-migrants which is not a possible effect of conflict is number of children. We control for this variable in our analysis.

[13]More on the capacity index and what is used in its computation can be found in the Table 23of the appendix. In the data section of the paper we describe how we impute the data on conflict and capacity into our census data for 2005.

[14]Enrollment, our focus in this paper, is inversely related to dropout rate.

attribute to conflict the impact of this pressure on drop out rates or enrollment. Although we think this kind of bias will be marginal, one way to deal with this potential bias is to use instrumental variables. We do not explore this route because we are unable find a suitable instrument that satisfies exclusion restriction and including a weak instrument could create more bias in our estimated coefficients than if an OLS estimate was derived.[15] Although Rodriguez and Sanchez (2009) use lagged homicide capture rates as an instrument, we are not of the opinion that this variable satisfies exclusion restrictions. One possible way to deal with this omitted variable which we explore in our paper is to restrict the sample to high conflict communities. In these communities, we can assume that the pressure to drop out should on average be the same. Hence, the estimated enrollment and attainment gaps for IDPs in comparison to non-migrants living in these high conflict region will not be upward biased because the missing variable has similar distribution across both groups.

We also explore a fixed effect technique to overcome this problem. Pressure to migrate and level of conflict should be similar across individuals within a municipality. This is because as Rodriguez and Sanchez (2009) note, pressure to migrate depends on level of conflict. Conflict, social and economic infrastructure, and other related variables that could potentially affect enrollment and accumulation are calculated at the municipality level and should not vary greatly across the municipality. We can therefore include fixed effects for all municipalities in our data. Of course, this problem will not deal with any omitted variable that may vary within the municipality if that variable is correlated with education outcomes and varies across IDPS and other groups. Although we cannot readily think of a variable that fits this category that we have not controlled for directly or indirectly (income), we cannot rule out this possibility.

# 6 Results

## 6.1 Does living in a high conflict area affect education outcomes?

The first question we try to answer as a motivation for our main question is if living in a high-conflict region leads to a gap in education. The purpose of this analysis is to compare the results to what has been noted in the prior literature on Colombia using other datasets. Figure 3 shows the density function for the conflict index. We designate any municipality with conflict over 0.3 as a region with high conflict. The mean conflict index is 0.276. Using this benchmark, 34.6% of the sample is exposed to high levels of conflict. We use this information to create a dummy variable which we include in our school accumulation and enrollment models. Individuals with a conflict index above 0.3 are assigned a 1 and all others are assigned a 0. Controlling for the factors that can

[15]See Staiger and Stock 1997 for more on weak instruments.

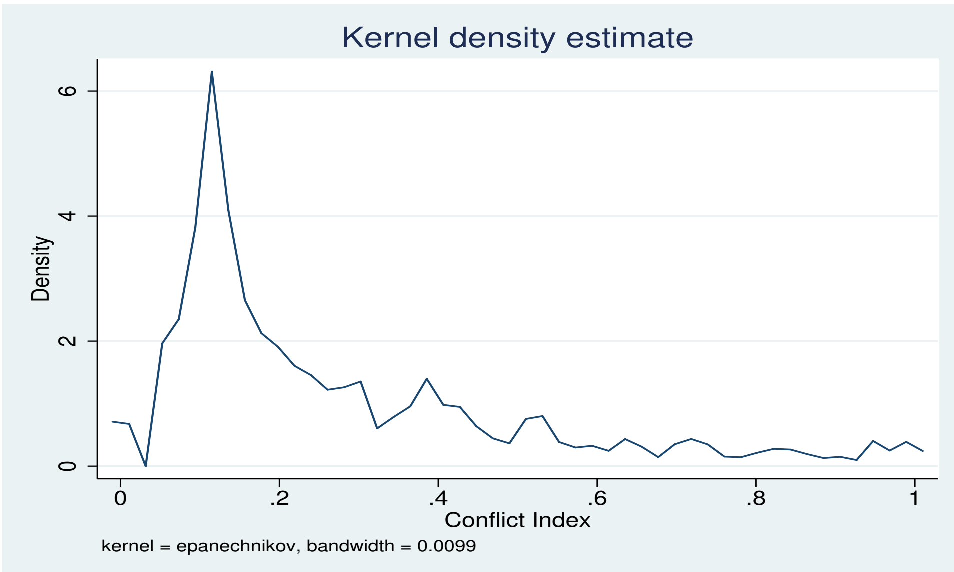


Figure 3: Kernel Density for Conflict Index

affect education outcomes both on the individual and regional scale, the results in Table 5 indicate that children who live in a high conflict region have about 0.04 fewer years of schooling than those living elsewhere. With respect to the probability of being enrolled, we note that children living in high conflict regions have a lower probability of being enrolled in school (0.8% and 0.9% lower at the elementary and secondary school levels respectively).Our results are quite different from those of Rodriguez and Sanchez (2009), who find that without conflict, the average education attainment of children between 6-11 years of age residing in conflict areas would have been 0.4 years higher, and for children between 12-17, 1.4 years higher. This difference in results is possible for several reasons. First, we look at the education gap by comparing children in high-conflict regions to those in lower-conflict municipalities, which is different from comparing children in high-conflict regions to a scenario with no conflict at all. Second, Rodriguez and Sanchez use a duration model to look at the effect of past exposure to conflict on the probability of dropping out of school, while we look at differences in education between children currently living in a high-conflict region compared to those living elsewhere. Finally, Rodriguez and Sanchez use the 2003 Colombia household survey covering 24,090 households in 128 municipalities, while we use the 2005 census with a sample size of 2,003,186 individuals across 533 municipalities. In a marked break with past research, our results suggest that living in a high-conflict area does not necessarily drive the education gap. In fact, when we cluster our standard error at the municipality level (because our conflict variable is at the

Table 5: Does living in a high conflict region affect education outcomes?

| | Age 6-11 | | Age 12-17 | |
|---|---|---|---|---|
| | Accumulation Model | Enrollment Model | Accumulation Model | Enrollment Model |
| Conflict Region | -0.036*** | -0.008*** | -0.036* | -0.009** |
| | (0.01) | (0.00) | (0.02) | (0.00) |
| N | 171083 | 171393 | 148447 | 148650 |
| F | 1794.31 | | 858.66 | |
| $P(F) > 0$ | 0.000 | | 0.000 | |
| $R^2$ | 0.661 | | 0.472 | |
| $\chi^2$ | | 5672.32 | | 7443.67 |
| $P > \chi^2$ | | 0.000 | | 0.000 |
| Pseudo $R^2$ | | 0.151 | | 0.196 |

Note: Also controlled for age, race, family size, disability, employment status of father, automobile ownership, wall type, computer ownership, class of father's work, class of mother's work, mother's number of children, and department.
Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

municipality level), we get no significant effects in all cases apart from the probability of enrollment for children ages 6-11 years.

It is also important to mention that our estimate could be biased because of the possible endogenous nature of the dummy variable for living in a high-conflict area. If living in a high-conflict area is correlated with an omitted variable that can affect education accumulation or enrollment, then the estimated coefficient could be biased. Although we control for many variables that could fit this profile with our capacity index,[16] one variable that we do not control for and that Rodriguez and Sanchez (2009) point to as potentially leading to lower schooling outcomes is pressure to join militant groups in high-conflict regions. Hence, if we do not control for this omitted variable, we could attribute to living in a conflict region the impact of the pressure to join militant groups.

Assuming that this is true, our estimated impact of living in a conflict region could be upward biased, implying an even smaller gap between children living in conflict region and children who do not. Another way to interpret these results is to think of the estimated impact as an upper limit on the difference as long as there is no omitted variable positively correlated with the dependent variable and exposure to conflict.[17]

The above results suggest living in a high-conflict municipality has only a very small effect on

[16]The capacity index is a measure of a municipality's infrastructure. We also tried alternative models with more poverty correlates like home ownership, floor type, number of rooms, and the result does not change significantly. Given this result, for the rest of the paper we restrict ourselves to just a few poverty correlates.

[17]We could not think of any such variable that we did not control for, but it is still a possibility.

education outcomes. This finding leads to our second question of how being directly affected by conflict impacts education accumulation and enrollment. Does it have a similar effect as living in a high-conflict municipality or do IDPs find themselves particularly disadvantaged in terms of schooling?

As highlighted in our model specification, we estimate an OLS regression, controlling for potential heteroskedasticity and controlling for the general predictors of school accumulation. For our enrollment model, we estimate a probit model and derive the marginal effects. In both cases, we divide the population into subgroups: non-recent migrants and recent migrants. The recent migrant subgroup is further divided by reason for migration by eight dummy variables: work migrants, family migrants, study migrants, natural disaster migrants, health migrants, other migrants, non-specified migrants, and our group of interest, IDPs. These dummies allow us to compare the different groups of migrants to a base group of non-migrants.

### 6.2 Results: School Accumulation Models

The results summarized in Tables 6-9 help us answer the question of whether there are education accumulation and enrollment gaps for IDP children in comparison to other migrant sub-groups. Specifically, Table 6 summarizes the results from our estimation of the school accumulation models based on equation (1), for ages 6-11, using ordinary least squares (OLS) and correcting for potential heteroscedasticity. We highlight the other control variables included in our estimation under the table.

In column (1), we control for age, sex, race, family size, sector (urban or rural), disability, employment status of father, class of work of father, class of work of mother, years of school of mother, year of school of father, number of children of mother, and department of residence. We also include some proxies for wealth because the census data does not have information on income. There were several potential variable that we could use as proxies. Our choice reflected variables that we believe could do a better job of capturing variation in wealth. These variables are number of cars, if an individual has a computer, and the type of walls of residence of an individual.[18] Although we are interested in the accumulation gap for IDPs in comparison to non-recent migrants, we also present the marginal effects for other recent migrant groups.[19] The results in column (1) do not control for conflict in the municipality or the social capacity in the municipality. Hence, estimates may exhibit upward bias.

[18] We chose these three proxy for wealth but our results for IDPs do not change significantly with alternative choice combination of potential wealth proxies like type of floor, having a toilet, ownership of dwelling, etc.

[19] For the rest of the paper, we will refer to non-recent migrants as non-migrants.

Table 6: Linear Regression Model Ages 6-11: Do migrants who move because of violence and insecurity face an education attainment gap compared to non-migrants?

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | All municipalities | All municipalities | All municipalities | Dept $conflict > 0.3$ | municipality $conflict > 0.3$ | municipality $conflict > 0.5$ |
| Work | -0.132*** | -0.132*** | -0.131*** | -0.195*** | -0.199*** | -0.169** |
| | (0.03) | (0.03) | (0.03) | (0.04) | (0.05) | (0.08) |
| Family move | -0.201*** | -0.201*** | -0.200*** | -0.218*** | -0.213*** | -0.228*** |
| | (0.01) | (0.01) | (0.01) | (0.02) | (0.02) | (0.03) |
| Study | -0.037 | -0.037 | -0.039 | -0.079 | -0.052 | -0.085 |
| | (0.05) | (0.05) | (0.05) | (0.07) | (0.07) | (0.10) |
| Violence | -0.199*** | -0.199*** | -0.197*** | -0.242*** | -0.218*** | -0.322*** |
| | (0.04) | (0.04) | (0.04) | (0.05) | (0.06) | (0.09) |
| Nat. disaster | -0.134*** | -0.134*** | -0.134*** | -0.184*** | -0.074 | -0.146 |
| | (0.05) | (0.05) | (0.05) | (0.07) | (0.07) | (0.10) |
| Health | -0.124** | -0.124** | -0.124** | -0.132 | -0.052 | -0.095 |
| | (0.06) | (0.06) | (0.06) | (0.10) | (0.12) | (0.18) |
| Other | -0.186*** | -0.187*** | -0.185*** | -0.212*** | -0.164*** | -0.150*** |
| | (0.02) | (0.02) | (0.02) | (0.03) | (0.04) | (0.05) |
| Not specified | -0.106 | -0.105 | -0.097 | -0.133 | -0.081 | -0.073 |
| | (0.09) | (0.09) | (0.09) | (0.13) | (0.14) | (0.16) |
| Sex | -0.133*** | -0.133*** | -0.133*** | -0.149*** | -0.164*** | -0.143*** |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.02) | (0.02) |
| Urban | 0.018* | 0.018* | 0.022** | 0.017 | 0.023 | 0.039 |
| | (0.01) | (0.01) | (0.01) | (0.02) | (0.02) | (0.03) |
| Mom yrs of sch. | 0.044*** | 0.044*** | 0.044*** | 0.050*** | 0.049*** | 0.051*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Dad yrs of sch. | 0.020*** | 0.020*** | 0.020*** | 0.018*** | 0.022*** | 0.024*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Conflict | | -0.012 | -0.060** | -0.005 | -0.015 | 0.074 |
| | | (0.02) | (0.02) | (0.03) | (0.04) | (0.08) |
| Capacity | | | 0.145*** | 0.167*** | 0.264*** | 0.209*** |
| | | | (0.03) | (0.04) | (0.05) | (0.06) |
| N | 171083 | 171083 | 171083 | 74212 | 56722 | 28071 |
| F | 1677.81 | 1657.45 | 1635.96 | 974.04 | 599.17 | 300.38 |
| $P(F) > 0$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| $R^2$ | 0.663 | 0.663 | 0.663 | 0.665 | 0.649 | 0.641 |

Note: Also controlled for age, race, family size, disability, employment status of father, automobile ownership, wall type, computer ownership, class of father's work, class of mother's work, mother's number of children, and department.
Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

These result suggests that children of IDPs between ages 6-11 have approximately 0.2 fewer years of schooling than non-migrants. When we add a control for conflict at the municipality level, we do not notice any change in the accumulation gap between children of IDPs and non-migrants (Table (6) column (2)). In the model captured in column (3), we also control for municipality capacity, which is a necessary control to reduce omitted variable bias in the estimate of the direct impact of conflict. Our dummy of interest does not differ considerably in column (3) from the two previous models. In comparison to Rodriguez and Sanchez (2009), our results suggest a smaller education gap. For children ages 6-11, they find that violence accounts for a 0.4 year decrease in schooling. However, this difference is not totally unexpected. We use a different technique, looking at IDPs directly rather than a duration analysis of municipality-level exposure to conflict. Also, because non-migrants may also be exposed to conflict, the gap between IDPs and non-migrants could be smaller than the gap created by exposure to conflict.

Notice that the education gap we find between IDPs and non-migrants is much larger than the gap between those living in high-conflict regions versus low-conflict regions shown in Table 5. This difference suggests that living in a high-conflict region may lead to slightly lower school attainment, but this factor is not nearly as significant at the 6-11 age group as being directly affected by conflict. Our high $R^2$s show that our model explains between 60-65% of the variation in school accumulation for children ages 6-11. Also recall that this estimated gap may form an upper limit to the potential accumulation gap if pressure to drop out of school is significant.

In Table 7, we summarize the results of similar models as in Table 6 but we restrict the sample to children ages 12-17. The trend in the estimates is the same. Although our $R^2$ drops, it is still relatively high. Focusing on column (3), our results suggests that children of IDPs ages 12-17 have about half a year gap in education accumulation in comparison to non-migrants. Notice that this gap is larger than the gap for the children of all the other migrant groups apart from those who migrated for unspecified reasons. Again, this gap is not directly comparable to the results of Rodriguez and Sanchez (2009), who find that exposure to armed conflict creates a 1.4 year gap for children ages 12-17.[20]

### 6.3 Results: School Enrollment Models

We move away from our education accumulation model and check to see if our enrollment model leads to similar conclusions about the education gap. First, we estimate the probability of being enrolled in school for children ages 6-11 (Table 8) and afterwards, we estimate our enrollment model for children ages 12-17 (Table 9). In contrast to the accumulation model for which we present

[20] Our base group non-migrant have not been directly affected by conflict, but could have been exposed to conflict.

Table 7: Linear Regression Model Ages 12-17: Do migrants who move because of violence and insecurity face an education attainment gap compared to non-migrants?

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | All municipalities | All municipalities | All municipalities | Dept $conflict > 0.3$ | municipality $conflict > 0.3$ | municipality $conflict > 0.5$ |
| Work | -0.453*** | -0.453*** | -0.454*** | -0.459*** | -0.468*** | -0.200 |
| | (0.06) | (0.06) | (0.06) | (0.09) | (0.12) | (0.13) |
| Family | -0.229*** | -0.230*** | -0.232*** | -0.263*** | -0.252*** | -0.206*** |
| | (0.03) | (0.03) | (0.03) | (0.04) | (0.05) | (0.07) |
| Study | 0.063 | 0.064 | 0.065 | -0.183* | -0.042 | 0.013 |
| | (0.08) | (0.08) | (0.08) | (0.11) | (0.14) | (0.17) |
| Violence | -0.513*** | -0.513*** | -0.515*** | -0.445*** | -0.560*** | -0.610*** |
| | (0.09) | (0.09) | (0.09) | (0.12) | (0.13) | (0.19) |
| Nat. disaster | -0.279* | -0.279* | -0.281* | -0.069 | -0.002 | -0.024 |
| | (0.15) | (0.15) | (0.15) | (0.15) | (0.18) | (0.15) |
| Health | -0.458*** | -0.458*** | -0.457*** | -0.095 | -0.350* | -0.378 |
| | (0.12) | (0.12) | (0.12) | (0.18) | (0.19) | (0.30) |
| Other | -0.218*** | -0.220*** | -0.222*** | -0.213*** | -0.186** | -0.160 |
| | (0.04) | (0.04) | (0.04) | (0.06) | (0.07) | (0.11) |
| Not spec | -0.713*** | -0.712*** | -0.722*** | -0.760** | -0.130 | -0.407 |
| | (0.22) | (0.22) | (0.22) | (0.31) | (0.28) | (0.45) |
| Sex | -0.495*** | -0.495*** | -0.494*** | -0.512*** | -0.503*** | -0.534*** |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.03) | (0.04) |
| Urban | 0.477*** | 0.478*** | 0.472*** | 0.565*** | 0.521*** | 0.526*** |
| | (0.02) | (0.02) | (0.02) | (0.03) | (0.04) | (0.05) |
| Mom yrs of sch. | 0.108*** | 0.108*** | 0.108*** | 0.107*** | 0.113*** | 0.108*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) |
| Dad yrs of sch. | 0.056*** | 0.056*** | 0.056*** | 0.058*** | 0.063*** | 0.077*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) |
| Conflict | | -0.148*** | -0.067 | -0.036 | -0.127* | 0.131 |
| | | (0.04) | (0.04) | (0.05) | (0.07) | (0.15) |
| CAP | | | -0.250*** | -0.234*** | -0.083 | 0.030 |
| | | | (0.06) | (0.08) | (0.09) | (0.12) |
| N | 148447 | 148447 | 148447 | 64052 | 48081 | 23326 |
| F | 795.21 | 785.77 | 777.69 | | 305.98 | 172.02 |
| $P(F) > 0$ | 0.000 | 0.000 | 0.000 | | 0.000 | 0.000 |
| $R^2$ | 0.474 | 0.474 | 0.474 | 0.476 | 0.476 | 0.487 |

estimates, for our enrollment model, in Tables 8 and 9 we present marginal effects. The results in column (3), our preferred model, suggest that children of IDPs ages 6-11 are 1.6% less likely to be enrolled in school in comparison to non-migrants. Table 8 summarizes the marginal effects for children ages 6-11.

Table 9 shows results of the probit model estimation for IDPs ages 12-17. We see an increase in enrollment gap compared to the younger age group, with IDP children ages 12-17 6.3% less likely to be enrolled than children of non-migrants. This finding is in line with Rodriguez and Sanchez (2009), who find much larger effects of exposure to conflict at the secondary level versus the primary level. One way to put this gap into perspective is to compare it to the enrollment gaps for other migrant groups. Because we do not control for selectivity of these migrant groups, we can think of the estimates as an upper boundary on education enrollment gaps for the other migrant groups. Notice that even the the enrollment gaps for children whose parents moved for work or because of natural disaster or health are smaller than the gap for IDP children.

The results above raise the question of what are the possible channels through which direct exposure to conflict leads to lower education accumulation and enrollment. IDPs lose assets and sources of income, which may create a constraint on future income streams and expenditures, including expenditure on children's education. However, this cannot be the only channel at work because those who migrate because of natural disaster are also likely to have lost assets and have constraints on their expenditures, yet their enrollment gap is not even statistically significant. Another possible explanation is that being directly affected by conflict leads to injury or death of family members. This could lead to reallocation of household duties, including children dropping out of school to care for a disabled family member or going to work. Table 1 seems to support this channel, showing that IDPs are more likely to be disabled. Another channel beyond the scope of economics could be the psychological impact of being directly affected by conflict. Combining this potential psychological effect with the two other highlighted channels and the disruption in education that comes with moving for exogenous reasons, one would expect the large gap in education accumulation and enrollment for IDP children compared to non-migrants and other migrant groups.

### 6.4 Results: Does living in a high-conflict municipality create a similar education gap as being displaced by conflict?

To answer the third question, we further investigate whether lower school attainment for IDPs is linked with being directly affected by conflict, living in a high-conflict area in the past, or a combination of both factors. We try to answer this question in several ways, starting with the assumption that if exposure to conflict alone (i.e. living in a high-conflict municipality) is the

Table 8: Probit Model Ages 6-11: Do migrants who move because of violence and insecurity face an enrollment gap compared to non-migrants?

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | All municipalities | All municipalities | All municipalities | Dept $conflict > 0.3$ | municipality $conflict > 0.3$ | municipality $conflict > 0.5$ |
| Work | -0.018*** | -0.018*** | -0.018*** | -0.027** | -0.031** | -0.021 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.02) |
| Family move | 0.003 | 0.003 | 0.003 | 0.004 | 0.003 | 0.000 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) | (0.01) |
| Study | 0.006 | 0.006 | 0.006 | 0.023*** | 0.020** | 0.024** |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Violence | -0.017* | -0.016* | -0.016* | -0.012 | -0.019 | -0.033* |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.02) |
| Nat. disaster | -0.006 | -0.007 | -0.007 | 0.013 | 0.001 | 0.014 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Health | -0.026* | -0.026* | -0.026* | -0.041 | -0.037 | -0.035 |
| | (0.02) | (0.02) | (0.02) | (0.03) | (0.04) | (0.05) |
| Other | 0.003 | 0.003 | 0.003 | 0.006 | 0.015 | 0.001 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.02) |
| Not specified | -0.065*** | -0.063*** | -0.062*** | -0.065*** | -0.019 | -0.016 |
| | (0.02) | (0.02) | (0.02) | (0.03) | (0.02) | (0.03) |
| Sex | -0.009*** | -0.009*** | -0.009*** | -0.007** | -0.009*** | -0.005 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Urban | 0.015*** | 0.015*** | 0.016*** | 0.017*** | 0.022*** | 0.031*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Mom yrs of sch. | 0.005*** | 0.005*** | 0.005*** | 0.006*** | 0.006*** | 0.007*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Dad yrs of sch. | 0.003*** | 0.003*** | 0.003*** | 0.003*** | 0.004*** | 0.003*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| CONF | | -0.017*** | -0.021*** | -0.022*** | -0.029*** | -0.038*** |
| | | (0.00) | (0.00) | (0.01) | (0.01) | (0.01) |
| CAP | | | 0.012** | 0.006 | 0.022** | 0.028** |
| | | | (0.01) | (0.01) | (0.01) | (0.01) |
| N | 171393 | 171393 | 171393 | 74322 | 56835 | 28136 |
| $\chi^2$ | 5699.98 | 5722.44 | 5709.09 | 2096.64 | 2580.28 | 1421.15 |
| $P > \chi^2$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Pseudo $R^2$ | 0.151 | 0.152 | 0.152 | 0.143 | 0.174 | 0.180 |

Note: Also controlled for age, race, family size, disability, employment status of father, automobile ownership, wall type, computer ownership, class of father's work, class of mother's work, mother's number of children, and department.
Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Probit Model Ages 12-17: Do migrants who move because of violence and insecurity face an enrollment gap compared to non-migrants?

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | All municipalities | All municipalities | All municipalities | Dept $conflict > 0.3$ | municipality $conflict > 0.3$ | municipality $conflict > 0.5$ |
| Work | -0.045*** | -0.045*** | -0.045*** | -0.045*** | -0.036** | -0.007 |
| | (0.01) | (0.01) | (0.01) | (0.02) | (0.02) | (0.02) |
| Family | -0.009 | -0.009 | -0.010 | -0.012 | -0.005 | -0.006 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.02) |
| Study | 0.007 | 0.007 | 0.007 | 0.037 | 0.036 | 0.047 |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.03) |
| Violence | -0.063*** | -0.063*** | -0.063*** | -0.060*** | -0.105*** | -0.107** |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.03) | (0.05) |
| Nat. disaster | -0.025 | -0.025 | -0.025 | -0.020 | -0.034 | -0.039 |
| | (0.02) | (0.02) | (0.02) | (0.03) | (0.03) | (0.04) |
| Health | -0.028* | -0.028* | -0.028* | -0.070** | -0.029 | -0.015 |
| | (0.02) | (0.02) | (0.02) | (0.03) | (0.03) | (0.04) |
| Other | 0.005 | 0.005 | 0.004 | 0.002 | 0.010 | 0.019 |
| | (0.01) | (0.01) | (0.01) | (0.02) | (0.02) | (0.02) |
| Not spec | -0.050 | -0.050 | -0.051 | -0.012 | 0.018 | -0.070 |
| | (0.04) | (0.04) | (0.04) | (0.05) | (0.05) | (0.08) |
| Sex | -0.042*** | -0.042*** | -0.042*** | -0.053*** | -0.049*** | -0.047*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) | (0.01) |
| Urban | 0.062*** | 0.063*** | 0.062*** | 0.081*** | 0.075*** | 0.075*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) | (0.01) |
| Mom yrs of sch. | 0.010*** | 0.010*** | 0.010*** | 0.010*** | 0.009*** | 0.010*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Dad yrs of sch. | 0.008*** | 0.008*** | 0.008*** | 0.008*** | 0.008*** | 0.008*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| CONF | | -0.025*** | -0.018** | -0.022** | -0.013 | 0.052* |
| | | (0.01) | (0.01) | (0.01) | (0.01) | (0.03) |
| CAP | | | -0.021** | -0.033** | -0.016 | 0.021 |
| | | | (0.01) | (0.01) | (0.02) | (0.02) |
| N | 148650 | 148650 | 148650 | 64136 | 48171 | 23384 |
| $\chi^2$ | 7366.80 | 7441.71 | 7444.77 | 3614.16 | 2679.77 | 1442.17 |
| $P > \chi^2$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Pseudo $R^2$ | 0.196 | 0.196 | 0.196 | 0.195 | 0.191 | 0.192 |

Note: Also controlled for age, race, family size, disability, employment status of father, automobile ownership, wall type, computer ownership, class of father's work, class of mother's work, mother's number of children, and department.
Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

primary cause of education gaps, then those who did not migrate but live in a high-conflict area should have similar education outcomes as IDPs in those areas. Hence, if we restrict our sample to only those living in areas with high conflict, the estimate on the IDP dummy should be 0 or close to 0. We explore three alternative ways of restricting the sample. Our conflict index runs from 0-1 with a mean of 0.28. In column (4) of Tables 6-9 we restrict our sample to departments with a mean conflict of over 0.3. This analysis leads to a reduction in the sample of departments in the analysis from 33 to 14. Focusing on Table 6 column (4), we find that children of IDPs living in high-conflict departments have a 0.24 fewer years of schooling than children of non-migrants who live in high-conflict departments. However, averaging over the state may be misleading. Restricting the sample based on high-conflict municipalities is more informative. In columns (5) and (6) of Tables 6-9, we restrict the sample to only those living in municipalities with a conflict index greater than 0.3 and 0.5 respectively. We still find that children of IDPs living in high conflict areas have a lower school attainment (Tables 6 and 7) and lower school enrollment (Tables 8 and 9). Specifically, we find that IDP children ages 6-11 living in high-conflict municipalities (conflict above 0.3) have 0.22 fewer years of schooling and a 1.9% lower probability of being enrolled in school (although the enrollment gap is not statistically significant) in comparison to non-migrants living in high conflict regions. For children of IDPs 12-17, the gap is larger: 0.56 fewer years of schooling and a 10.5%lower probability of being enrolled.

It is worth noting from Tables 6 and 7 that the gap in education accumulation increases when we focus on municipalities with very intense conflict (index $> 0.5$). For ages 6-11, the gap increases by 0.10 to 0.32 years, and for ages 12-17, the gap increases by 0.05 to 0.61 years. We note a further decrease in probability of enrollment in municipalities with very intense conflict, as well (see Tables 8 and 9).

These results combined with the results in Table 5 provide evidence that though municipality-level exposure to conflict could affect education accumulation and enrollment for children, being directly affected by conflict impacts these outcomes more significantly. Simply accounting for municipality-level exposure to conflict does not adequately measure the education impact of violence, particularly in the context of a low-intensity conflict as in Colombia.

### 6.5 Results: How do IDPs compare to other migrants?

Finally, we address the question of how IDPs compare to other other migrants in terms of education accumulation and enrollment. The results are summarized in Tables 10 and 11. Focusing on migrants is useful for several reasons. First, it is possible to argue that IDPs are migrants, and so comparing them with other migrants is more appropriate. In all of the previous tables, children of most migrant groups have lower accumulation and enrollment than non-migrants. Hence, one could argue that the gap between IDP children and non-migrant children could be attributed part to migrant selection. For example, children whose parents or themselves migrated for study do not exhibit the same education gap as other migrant groups. While the argument of selectivity has credibility for most migrant groups, IDPs and natural disaster migrants are different because they move as a result of exogenous factors. Although it may be safe to assume that selectivity is not an issue for IDPs and migrants linked to natural disaster, as long as not every person affected by the exogenous shock of conflict migrates, we cannot fully rule out issues of selectivity.

Another related argument is that even if IDPs are not a select group like other categories of migrants, the act of migrating itself may lead to disruption in schooling and thus lower education outcomes. The problem with this argument is that it does not hold for all groups of migrants. If there is no selectivity issue and all migrants faced equal disruption in schooling from the act of migrating, then ceteris paribus, we should see similar education gaps across all groups when compared to non-migrants. This is not what we see in Tables 6-9. The education accumulation and enrollment gaps vary greatly across groups of migrants. The suggestion that reason for migrating matters motivates our final question. As noted in the empirical strategy section, we focus this analysis first on recent migrants because we can only identify recent IDPs. However, we then compare recent IDPs to anyone who has migrated over their lifetime.[21] Table 10 summarizes the results for children ages 6-11, and Table 11 summarizes the results for ages 12-17.

The results in Tables 10 and 11 provide support for our earlier conclusion about the direct impact of conflict. We find that even when we compare IDPs to other migrants, who are a select group with lower education accumulation and enrollment on average than non-migrants, we still notice accumulation and enrollment gaps for IDPs children ages 12-17.[22] However, we find that for children 6-11 years, the gap is present but not significant except in column (5). However, if we extend the sample to all migrants–recent or not recent (see Tables 20 and 21 in the appendix), we notice a small but statistically significant gap in accumulation and enrollment. In contrast, when we look at ages 12-17 in Table 11, the education gap is larger and statistically significant. When IDPs of this age group are compared to other migrants instead of non-migrants, the education accumulation gap shrinks by 0.15 years to 0.34, and the enrollment gap shrinks by 2.2% to 4.1%. The results from the analysis focused solely on migrants suggests that the education gap exhibited by IDP children is not

[21] We are able to identify all migrants by comparing where in individual lives now to were they were born. If these two municipalities are different, we include this person in the sample. We then compare IDPs to all other migrants.

[22] This gap is not created by children of migrants who move for study and are likely to have higher education outcomes than other migrants. To verify this, we drop these children from our analysis. The estimated gap is not statistically different with or without them.

Table 10: Are IDPs different? Ages 6-11

| | Education Accumulation Model | | | School Enrollment Model | | |
|---|---|---|---|---|---|---|
| | All Migrants | Migrants Conf > 0.3 | All obs with Conf > 0.3 | All Migrants | Migrants Conf > 0.3 | All with Conf > 0.3 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| IDP | -0.042 | -0.067 | -0.105** | -0.010 | -0.022** | -0.008 |
| | (0.04) | (0.06) | (0.04) | (0.01) | (0.01) | (0.01) |
| Sex | -0.101*** | -0.131*** | -0.166*** | -0.010*** | -0.012** | -0.010*** |
| | (0.02) | (0.03) | (0.02) | (0.00) | (0.01) | (0.00) |
| Conflict | 0.011 | 0.007 | -0.023 | -0.009 | -0.019 | -0.032*** |
| | (0.05) | (0.08) | (0.04) | (0.01) | (0.01) | (0.01) |
| Capacity | 0.044 | 0.138 | 0.286*** | 0.002 | 0.000 | 0.022** |
| | (0.07) | (0.10) | (0.05) | (0.01) | (0.02) | (0.01) |
| Urban | 0.044** | 0.075** | 0.009 | 0.014*** | 0.025*** | 0.023*** |
| | (0.02) | (0.04) | (0.02) | (0.00) | (0.01) | (0.00) |
| Mom Yrs of sch. | 0.037*** | 0.036*** | 0.049*** | 0.004*** | 0.004*** | 0.007*** |
| | (0.00) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) |
| Dad Yrs of sch. | 0.020*** | 0.027*** | 0.021*** | 0.003*** | 0.003*** | 0.003*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | 0 |
| N | 34457 | 11410 | 57815 | 34459 | 11428 | 57893 |
| F | 453.48 | 170.13 | - | | | |
| $P > (F)$ | 0.000 | 0.000 | - | | | |
| $R^2$ | 0.700 | 0.684 | 0.647 | | | |
| $\chi^2$ | | | | 1299.79 | 553.27 | 2541.03 |
| $P > (\chi^2)$ | | | | 0.000 | 0.000 | 0.000 |
| $Pseudo R^2$ | | | | 0.157 | 0.144 | 0.173 |

Note: Also controlled for age, race, family size, disability, employment status of father, automobile ownership, wall type, computer ownership, class of father's work, class of mother's work, mother's number of children, and department.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In column (3) and (6) we are comparing all IDPs with both migrants and non-migrants living in a region with high conflict.

a gap linked with simply being a migrant because this gap persists when the sample is restricted to only migrants. However, because the magnitude of the gap decreases, there may be some negative selection bias across migrant groups with respect to education.

To address any potential selectivity bias that may arise in Table 6-9 columns (4)-(6) when we compare IDPs to non-migrants living in high conflict areas, we also restrict our migrants to those living in high-conflict areas and compare them to IDPs. Because everyone in the sample migrated to a high-conflict region, the selectivity argument cannot be made. The results in Tables 10 and 11 columns (2) and (5) suggest that for children ages 6-11, there is no difference in education accumulation between those whose who are directly affected by conflict and those who are exposed to conflict, but IDPs have a 2.2% lower probability of being enrolled in school. When we consider children 12-17, the results are more consistent across both the accumulation and enrollment models. We find that IDP children have about 0.4 fewer years of schooling and are 8.8% less likely to be enrolled in school. This large gap could suggest one of two things. First, living in a conflict region is only marginally important for education accumulation and enrollment, as noted in Table 5 and confirmed here. What is important is being directly affected by conflict especially in the older age group. Second, given that children of migrants living in high-conflict areas still have better education outcomes than IDPs, the channel that leads to lower school accumulation and enrollment in IDPs cannot be explained solely by migration or disruption in schools because of living in a conflict area. Rather, loss of income of parents, lower probability of employment of parents or care givers who become disabled because of conflict, and psychological factors linked with being directly affected by conflict are more likely explanations for this gap.

In columns (3) and (6) of Tables 10 and 11, we compare all IDPs with other migrants who live in high conflict regions. This is another robustness check to avoid the possible argument that when we compared IDPs living in conflict regions with other migrants in those regions, we might be dealing with a select type of IDP. Because the previous scenario looks at IDPs who migrated to avoid conflict yet still end up living in a high-conflict region, we may be looking at particularly vulnerable IDPs. By comparing all IDPs, regardless of current residence, to migrants living in high-conflict regions, we avoid this potential issue.

The results in columns (3) and (6) suggest that children of IDPs ages 6-11 have about 0.1 fewer years of schooling than other migrant children living in high-conflict municipalities but similar probability of being enrolled in school. Children of IDPs ages 12-17 have 0.44 fewer years of schooling and a 5.7% lower probability of being enrolled. We see that the education gap shrunk somewhat in this model, suggesting that IDPs living in a high-conflict municipalities are to some extent different from the average IDP.

Table 11: Are IDPs different? Ages 12-17

| Variable: | Education Accumulation Model | | | School Enrollment Model | | |
|---|---|---|---|---|---|---|
| | All Migrants | Migrants Conf > 0.3 | All obs with Conf > 0.3 | All Migrants | Migrants Conf > 0.3 | All with Conf > 0.3 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| IDP | -0.341*** | -0.395*** | -0.443*** | -0.041*** | -0.088*** | -0.057*** |
| | (0.09) | (0.14) | (0.09) | (0.02) | (0.03) | (0.02) |
| Sex | -0.427*** | -0.429*** | -0.506*** | -0.029*** | -0.039*** | -0.050*** |
| | (0.03) | (0.06) | (0.03) | (0.01) | (0.01) | (0.01) |
| Conflict | -0.030 | 0.015 | -0.131* | -0.014 | -0.020 | -0.019 |
| | (0.10) | (0.17) | (0.07) | (0.02) | (0.03) | (0.01) |
| Capacity | -0.305** | -0.404* | -0.054 | -0.032 | -0.005 | -0.016 |
| | (0.14) | (0.21) | (0.09) | (0.02) | (0.04) | (0.02) |
| Urban | 0.473*** | 0.529*** | 0.502*** | 0.069*** | 0.085*** | 0.076*** |
| | (0.05) | (0.08) | (0.04) | (0.01) | (0.01) | (0.01) |
| Mom yrs of sch. | 0.092*** | 0.088*** | 0.114*** | 0.009*** | 0.008*** | 0.010*** |
| | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) |
| Dad Yrs of sch. | 0.050*** | 0.061*** | 0.062*** | 0.007*** | 0.010*** | 0.008*** |
| | (0.01) | (0.01) | (0.00) | (0.00) | | (0.00) |
| N | 24124 | 8116 | 48960 | 24155 | 8110 | 49048 |
| F | 168.88 | 71.87 | - | | | |
| P(F) | 0.000 | 0.000 | - | | | |
| $R^2$ | 0.492 | 0.481 | 0.476 | | | |
| $\chi^2$ | | | | 1646.86 | 690.64 | 2658.44 |
| $P > (\chi^2)$ | | | | 0.000 | 0.000 | 0.000 |
| Pseudo $R^2$ | | | | 0.203 | 0.207 | 0.190 |

Note: Also controlled for age, race, family size, disability, employment status of father, automobile ownership, wall type, computer ownership, class of father's work, class of mother's work, mother's number of children, and department.
In column (3) and (6) we are comparing all IDPs with both migrants and non-migrants leaving in a region with high conflict. Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

## 6.6 Robustness checks: Are the results driven by sampling bias?

The analyses above suggest that being directly affected by conflict affects children's probability of being enrolled in school at both the elementary level and secondary level. It also affects their education accumulation. However, the effect on younger children is smaller and not always significant. On the other hand, the gaps for older children are consistently significant and of greater magnitude. Although we find that some other migrant groups on average have lower levels of education, and those living in high-conflict municipalities in general have slightly lower education accumulation and enrollment, the gap does not compare to that faced by IDPs. Still, one might raise the question of whether this persisting gap in education for IDPs is driven by some omitted variable that is

Table 12: Who are we capturing?

| Age | Total | With Both Parents | Percentage |
|---|---|---|---|
| 6-11 | 261,469 | 180,912 | 69.19% |
| 12-17 | 250,349 | 158,347 | 63.25% |

correlated with being directly affected by conflict. We are of the opinion that this is not the case for several reasons.

First, although it is impossible to control for all possible factors that affect education outcomes, we are able to control for most of the factors that have been shown in past empirical and theoretical literature to be important for enrollment and accumulation. Our relatively high R-squared is one indicator that our education accumulation model is relevant and explains a significant portion of the variation in schooling and enrollment. Second, although there are other possible variables that we do not control for, such as ability, we are not worried because their distribution should be similar among IDPs and the comparison groups. In this scenario, the estimated education gap would not be biased by their omission.

It is important to mention that our inclusion of some important variables that predict enrollment and accumulation creates secondary effects. We control for parents' education, and not every child in the sample has this information available. Because we include the variable for parents' education, the analyses above are not conducted on the whole sample of children ages 6-17. Table 12 provides a breakdown of the percentage of children included for each age cohort. We use 69% of the sample ages 6-11 and 63% of the sample ages 12-17, raising the question of whether an analysis on the entire sample would lead to a different outcome.

To investigate this possibility, we estimate the bias created in our estimate of the gap if we do not include all the parent related variables. To find this bias, we first re-estimate our accumulation and enrollment models with and without the parental variables, including both migrants and non-migrants and restricting our sample to those who have parent information. The results from this analysis are summarized in Tables 13 and 14. Notice that the results in columns (1) and (4) are a repetition of earlier analysis and the results in column (2) and (5) are the estimated coefficients if parental controls are not included for the same sample. The upward bias in the estimates is significant if we do not include parental controls. Specifically for children 6-11, without parental controls we overestimate the impact of direct contact with violence on school accumulation by 0.071 years and overestimate the probability of enrollment gap for those affected by violence by 1.3%.

For children 12-17, if we do not include parental controls, we overestimate the direct impact

Table 13: Education Gap: Parental Controls v. No Parental Controls (Ages 6-11)

| | Education Accumulation Model | | | Probability Model | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Parental control | No Parental controls | Difference (2) - (1) | Parental controls | No Parental controls | Difference (5) - (4) |
| IDP | -0.197*** | -0.268*** | 0.071 | -0.016* | -0.029*** | 0.013 |
| | (0.04) | (0.04) | | (0.01) | (0.01) | |
| N | 171083 | 171083 | | 171393 | 171393 | |
| F | 1635.96 | 1677.78 | | | | |
| $P > (F)$ | 0.000 | 0.000 | | | | |
| $R^2$ | 0.663 | 0.648 | | | | |
| $\chi^2$ | | | | 5709.09 | 5571.68 | |
| $P > \chi^2$ | | | | 0.000 | 0.000 | |
| $PseudoR^2$ | | | | 0.152 | 0.123 | |

Note: Also controlled for sex, conflict, capacity, urban, mothers years of schooling and fathers years of schooling, age, race, family size, disability, employment status of father, automobile ownership, wall type, computer ownership, class of father's work, class of mother's work, mother's number of children, state and reasons for migration.
Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Base group: non-migrants.

of violence on school accumulation by 0.177 years and overestimate the enrollment gap by 2.2%. Given our knowledge of the potential bias caused by not including parental controls, we re-estimate equation (2) without parental controls on the whole sample. This means that the observations that were not included previously because of missing information about parental controls are now included in the analysis. The results are summarized in Table 15 columns (1), (3), (5) and (7). Notice that for the children 6-11 years old, these estimates are very similar to the estimates we got for the sample that have parental information when parental controls were dropped and the gap estimated. For secondary school age children, the difference is slightly larger.

In columns (2), (4), (6) and (8), we present the corrected estimate of the education accumulation and enrollment gaps using the estimated effect of not including parental controls highlighted in Tables 13 and 14. These bias correct estimates will be valid as long the distribution when we use the sample with parent control is no different from the distribution when we use the whole sample. One way to check for the non-selectivity of the sample without parental controls is to test for differences in means on a set of demographic and economic variables for the sample with parental controls and the whole sample, restricting these samples to children ages 6-11 and 12-17. We find that the means are almost identical for all variables except family size. For family size, the ages 6-11 sample with parental controls has a mean of 5.7, while the mean for the whole sample is 5.5. In the

Table 14: Education Gap: Parental Controls v. No Parental Controls (Ages 12-17)

| | Education Accumulation Model | | | Probability Model | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Parental control | No Parental controls | Difference (2) -(1) | Parental controls | No Parental controls | Difference (5) - (4) |
| IDP | -0.515*** | -0.692*** | 0.177 | -0.063*** | -0.085*** | 0.022 |
| | (0.09) | (0.10) | | (0.02) | (0.02) | |
| N | 148447 | 148447 | | 148650 | 148650 | |
| F | 777.69 | 734.11 | | | | |
| $P(F) > 0$ | 0 | 0 | | | | |
| $R^2$ | 0.4741 | 0.4366 | | | | |
| $\chi^2$ | | | | 7444.77 | 7696.18 | |
| $P > \chi^2$ | | | | 0 | 0 | |
| Pseudo $R^2$ | | | | 0.1964 | 0.1752 | |

Note: Also controlled for sex, conflict, capacity, urban, mothers years of schooling and fathers years of schooling, age, race, family size, disability, employment status of father, automobile ownership, wall type, computer ownership, class of father's work, class of mother's work, mother's number of children, state and reasons for migration.
Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Base group: non-migrants. The sample above is restricted to those who have parental controls only.

12-17 years range, the sample with parental controls has a mean of 5.9, while the sample without parental controls has a mean of 5.3. The result of our means test suggests that the sample without parental controls is very similar to the sample with parental controls, particularly for the 6-11 age range.

## 6.7 Robustness checks: Fixed Effects

One possible argument against the validity of our above results is that we do not control for factors within communities that could affect enrollment and attainment. If IDPs live in communities with lower access to schools or lower social capacity and infrastructure, then the estimated gap compared to nonmigrants could be capturing these the effects of these community-level differences and not the direct effect of conflict. We address this potential issue by estimating our attainment model using fixed effects. The choice of this technique eliminates potential bias caused by omitted variables at the community (municipality) level. For example, pressure to leave school was one of the potential omitted variables we try to deal with by looking solely at municipalities with high conflict. However, it is possible to argue that not all high-conflict regions face similar pressure to drop out, so the problem of this omitted variable still persists. Another possible argument is that although we control for capacity and conflict using the HSRI indices, the use of these indexes which are a composite of

Table 15: Estimated education gap between IDPs and non-migrants for samples with and without parental controls

| | Age 6-11 | | | | Age 12-17 | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Yrs of sch. | Yrs of sch Corrected | Enroll | Enroll Corrected | Yrs of sch. | Yrs of sch Corrected | Enroll Enroll | Enroll Corrected |
| Violence | -0.264*** | -0.193 | -0.029*** | -0.016 | -0.669*** | -0.492 | -0.073*** | -0.051 |
| | (0.04) | | (0.01) | | (0.09) | | (0.02) | |
| N | 184128 | | 184878 | | 160686 | | 161497 | |
| F | 1759.36 | | | | 787.88 | | | |
| $P(F) > 0$ | 0.00 | | | | 0.000 | | | |
| $R^2$ | 0.64 | | | | 0.424 | | | |
| $\chi^2$ | | | 8119.97 | | | | 8735.37 | |
| $P > \chi^2$ | | | 0.000 | | | | 0.000 | |
| Pseudo $R^2$ | | | 0.135 | | | | 0.172 | |

Note: Also controlled for sex, conflict, capacity, urban, age, race, family size, disability, automobile ownership, wall type, computer ownership, state and reasons for migration.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

several other variables might not still be an effective control for the differences in conflict, social and economic capacity across municipalities. To show that our results are not driven by measurement error or by omitted variables that vary at the municipality level, we introduced a fixed effect for municipalities. Still, the use of municipality fixed effects does not deal with any omitted variable that varies within the municipality. We have controlled for such variables in our analysis to the extent possible. For other variables that might affect education outcomes, such as ability, we assume take the same distribution across comparison groups, and so they would not introduce bias in estimating the education gap.

Table 16 confirms our earlier results. In columns (1) and (2), we summarize the results comparing IDPs to the base group of non-migrants. In columns (3) and (4), we compare IDPs solely to other migrants. The results in Table 16 are our preferred estimates and suggest that children ages 6-11 who are directly exposed to conflict have 0.2 fewer years of schooling than non-migrants, and IDP children ages 12-17 have 0.49 fewer years of schooling. Looking solely at migrants, we do not find evidence of a statistically significant gap for younger children, but we do find evidence of a gap of 0.28 years among older children.

We are unable to use the fixed effect technique for the probit model. A not so perfect alternative is to estimate a linear probability model. Although the linear probability specification of the binary choice model provides ease of interpretation, unless restrictions are placed on estimates, coefficients

Table 16: Does being directly affected by conflict create an education gap (Fixed Effects)?

| | IDP v. non-migrants | | IDP v. other migrants | |
|---|---|---|---|---|
| | 6-11 | 12- 17 | 6-11 | 12- 17 |
| | (1) | (2) | (3) | (4) |
| Violence | -0.199*** | -0.487*** | -0.035 | -0.277*** |
| | (0.02) | (0.05) | (0.02) | (0.05) |
| Sex | -0.163*** | -0.588*** | -0.133*** | -0.509*** |
| | (0.01) | (0.01) | (0.01) | (0.02) |
| Urban | 0.048*** | 0.442*** | 0.036** | 0.385*** |
| | (0.01) | (0.01) | (0.01) | (0.03) |
| Mother Yrs sch. | 0.054*** | 0.134*** | 0.048*** | 0.121*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Father Yrs sch. | 0.026*** | 0.073*** | 0.020*** | 0.064*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| N | 171083 | 148447 | 34457 | 24124 |
| F | 777.69 | 752.89 | | |
| $P(F) > 0$ | 0.000 | 0.000 | 0.000 | 0.000 |
| $R^2$ | 0.620 | 0.430 | 0.650 | 0.450 |
| $\chi^2$ | | | | |
| $P > \chi^2$ | | | | |
| Pseudo $R^2$ | | | | |

Note: Also controlled for age, race, family size, disability, employment status of father, automobile ownership, wall type, computer ownership, class of father's work, class of mother's work, mother's number of children. In columns (1) and (2) we control for migration status, so dummies for other types of migrants are estimated but not presented. The base group is non-migrants. In columns (3) and (4) we have a binary indicator $IDP = 1$ and Other $migrants = 0$
Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

can imply probabilities outside the unit interval. Table 17 shows the results of the estimation of the enrollment model using fixed effects and assuming a linear probability model. These estimates provide some evidence of an enrollment gap but the evidence is mixed. We are more cautious about interpreting these estimates given the potential issue of the linear model itself.

One could also argue that birthplace municipality level factors matter more than current municipality. While we are not of this opinion, we provide a summary in Table 18 of fixed effect analyses using municipality of birth. The results are very similar to those using current municipality.

Table 17: Does being directly affected by conflict create an enrollment gap (Linear probability model with Fixed Effects)?

| | IDP v. non-migrants | | IDP v. other migrants | |
|---|---|---|---|---|
| | 6-11 | 12- 17 | 6-11 | 12- 17 |
| | (1) | (2) | (3) | (4) |
| Violence | -0.009 | -0.026*** | -0.010* | -0.014 |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| sex | -0.013*** | -0.058*** | -0.012*** | -0.050*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| urban | 0.037*** | 0.087*** | 0.040*** | 0.104*** |
| | (0.00) | (0.00) | (0.00) | (0.01) |
| Mother Yrs sch. | 0.007*** | 0.011*** | 0.007*** | 0.011*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Father Yrs sch. | 0.003*** | 0.007*** | 0.003*** | 0.007*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| N | 171393 | 148650 | 34510 | 24158 |
| F | 284.82 | 530.42 | 63.28 | 97.43 |
| $P(F) > 0$ | 0.000 | 0.000 | 0.000 | 0.000 |
| $R^2$ | 0.099 | 0.172 | 0.916 | 0.169 |
| Pseudo $R^2$ | | | | |

Note: Also controlled for age, race, family size, disability, employment status of father, automobile ownership, wall type, computer ownership, class of father's work, class of mother's work, mother's number of children.
In columns (1) and (2) we control for migration status, so dummies for other types of migrants are estimated but not presented. The base group is non-migrants. In columns (3) and (4) we have a binary indicator $IDP = 1$ and Other $migrants = 0$
Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

# 7 Summary and Conclusion

This paper is motivated by the idea that in low-intensity conflicts, not ever person living in a supposedly high-conflict area is equally affected. While past research tends to look at the impact of exposure to conflict alone on education, we investigate the question of how being directly affected by conflict (i.e. being an IDP) affects education outcomes.

In this paper, we answer four questions related to the impact of conflict on education. Our first question asks if there is an education gap for children living in municipalities with high conflict in comparison to those living elsewhere. Second, we ask if there is an education gap for IDP children. Third, we ask if living in a high-conflict municipality creates a similar education gap as being directly

Table 18: Does being directly affected by conflict create an enrollment gap-Estimates using Birth Place Municipality Fixed Effects?

| | IDP versus non-migrants | | IDP versus other migrants | |
|---|---|---|---|---|
| | 6-11 year old | 12- 17 year old | 6-11 year old | 12- 17 year old |
| | (1) | (2) | (3) | (4) |
| | | (Attainment GAP) | | |
| Violence | -0.212*** | -0.446*** | -0.045* | -0.222*** |
| | (0.02) | (0.05) | (0.03) | (0.06) |
| N | 171083 | 148447 | 34457 | 24124 |
| | | (Enrollment GAP) | | |
| Violence | -0.009 | -0.026*** | -0.010* | -0.014 |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| N | 171393 | 148650 | 34510 | 24158 |

In column (1) and (2) we control for migration status so dummies for other types of migrants are estimated but not presented. The base group is non-migrants. In column (3) and (4) we have a binary indicator $IDP = 1$ and Other $migrants = 0$
Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

affected by conflict. Finally, we ask how IDPs compare to other migrants with regard to education outcomes.

Using OLS and probit analyses, we find that although there appears to be a gap in accumulation and enrollment for children of those who live in high-conflict municipalities compared to those living elsewhere, this gap does not appear to be robust. Next, we find evidence of education accumulation and enrollment gaps for IDP children in comparison to non-migrants. We also find that living in a high-conflict area does not create an identical effect as being directly affected by conflict. An education gap persists and in fact grows when we compare IDPs to non-migrants living in high-conflict regions. Similarly, the gap between IDPs and other migrants living in high-conflict areas is larger than the gap between IDPs and all migrants, although the gap at the primary school level is not always significant. Finally, our results suggest that in general, IDP children fare worse than other migrant children with respect to education accumulation and enrollment. This result is robust to dropping school migrants from the dataset. We test the robustness of our results using fixed effects, and though the estimates differ slightly, the basic inference of a significant impact of being directly affected by conflict persists, particularly at the secondary level.

Several conclusions can be drawn from these results. First, having a parent who was directly affected by conflict negatively affects a child's education accumulation and enrollment. This gap grows as the child grows older. In contrast, mere exposure to conflict as captured by living in a high-conflict area does not seem to have as much impact on a child's education outcomes. Given the large literature that estimates the impact of conflict using exposure, our results suggest the need to isolate those directly affected by conflict and collect more data on their specific experiences. This kind of data would be useful in helping to create a framework for better understanding the channels through which being directly affected by conflict affects education and other labor market outcomes. Finally, while the above conclusions are most relevant for studies looking at low-intensity conflict, it is likely that they are also applicable to other types of conflict, such as high-intensity interstate or civil war.

# References


[1] Akresh, Richard and Damien de Walque (2008). Armed Conflict and Schooling: Evidence from the 1994 Rwandan Genocide. The World Bank, Policy Research Working Paper Series: 4606.

[2] Angrist, Joshua, Eric Bettinger, and Michael Kremer (2006). Long-Term Consequences of Secondary School Vouchers: Evidence from Administrative Records in Colombia. *The American Economic Review*, 96(3), 847-862.

[3] Angrist, Joshua, Eric Bettinger, Erik Bloom, Elizabeth King, and Michael Kremer (2002). Vouchers for Private Schooling in Colombia: Evidence from a Randomized Natural Experiment. *The American Economic Review*, 92(5): 1535-1558.

[4] Barrera-Osorio, Felipe, and Ana Maria Ibáñez (2004). Does Violence Reduce Investment in Education?: A Theortetical and Empirical Approach. *Documentos CEDE 002382*, Universidad de los Andes-CEDE.

[5] Chamarbagwala, Rubiana, and Hilc'as E. Morán (2011). The human capital consequences of civil war: Evidence from Guatemala. *Journal of Development Economics*, 94(1): 41-61.

[6] Dueñas, Lusia Fernanda and Fabio Sanchez (2007). Does Armed Conflict Affect the Poorest?: The Case of School Dropout in Eastern Colombia. Working Paper, Universidad de los Andes.

[7] Duryea, Suzanne, David Lam, and Deborah Levison (2001). Effects of Economic Shocks on Children's Employment and Schooling in Brazil. *Journal of Development Economics*, 84(1):pp 188-214.

[8] Evans, David K., and Edward Miguel (2007). Orphans and Schooling in Africa: A Longitudinal Analysis. *Demography*, 44(1): 35-57.

[9] Glewwe, Paul, and Hanan Jacoby (1994). Student Achievement and Schooling Choice in Low-Income Countries: Evidence from Ghana. *The Journal of Human Resources*, 29(3): 843-864.

[10] Gaston, Noel, and Jaime Tenjo (1992). Education Attainment and Earnings Determination in Colombia. *Economic Development and Cultural Change*, 41:pp 125-139.

[11] Ibánez, Ana Maria, and Andres Moya (2006). Como el Desplazamiento Forzado Deteriora el Bienestar de los Hogares Desplazados?: Analisis y Determinantes del Bienestar en los Municipios de Recepcion. Documento CEDE No. 2006-26. Universidad de los Andes.

[12] Ibáñez, Ana Maria, and Andres Moya (2009). Vulnerability of Victims of Civil Conflicts: Empirical Evidence for the Displaced Population in Colombia. *World Development*, 38(4): 647-663.

[13] Jacoby, Hanan G., and Emmanuel Skoufias (1997). Risk, Financial Markets, and Human Capital in a Developing Country. *Review of Economic Studies*, 64(3): 311-335.

[14] Kirchhoff, Stefanie, and Ana Maria Ibáñez (2002). Displacement due to Violence in Colombia: Determinates and Consequences at the Household Level. Discussion Papers 18754, University of Bonn, Center for Development Research (ZEF).

[15] Lozano-Gracia, Nancy, and Gianfranco Piras, Ana Maria Ibáñez, and Geoffrey J.D. Hewings (2010). The Journey to Safety: Conflict-Driven Migration Flows in Colombia. *International Regional Science Review*, 33(2): 157-180.

[16] McKenzie, David, and Hillel Rapoport (2010). Can Migration Reduce education Attainment? Evidence from Mexico. *Journal of Population Economics*, 24(4): 1331-1358.

[17] Poveda, Alexander Cotte, and Jin Anthony Cotrino Sossa (2006). Crecimiento Econ—mico y Distribuci—n del Ingreso en Colombia: Evidencia Sobre el Capital Humano y el Nivel de Educaci—n. Serie de Documentos en Economia y Violencia 002221, Centro de Investigaciones en Violencia, Instituciones y Desarrollo Economico (VIDE).

[18] Psacharopoulos, George & Velez, Eduardo, (1992). Schooling, Ability, and Earnings in Colombia, 1988, *Economic Development and Cultural Change*, University of Chicago Press, vol. 40(3), pages 629-43, April.

[19] Psacharopoulos, George & Eduardo Velez (1993). education Quality and Labor Market Outcomes: Evidence from Bogota, Colombia. *Sociology of Education*, 66(2): 130-145.

[20] Psacharopoulos, George. (1994). Returns to Investment in Education: A Global Update. World Development 22(9): 1325-43.

[21] Rodriguez, Catherine and Fabio Sanchez (2009). Armed Conflict Exposure, Human Capital Investments and Child Labor: Evidence from Colombia. HiCN Working Papers, 68.

[22] Staiger, D. and Stock, J., (1997). Instrumental Variable Regression with Weak Instruments. *Econometrica* 65:557-586.

[23] Shemyakina, Olga (2011). The Effect of Armed Conflict on Accumulation of Schooling: Results from Tajikistan. *Journal of Development Economics*, 95(2): 186-200.

[24] Thomas, Duncan, Kathleen Beegle, Elizabeth Frankenberg, Bondan Sikoki, John Strauss and Graciela Teruel (2004). Education in a Crisis. *Journal of Development Economics*, 74 (1):53-85. 2004.

[25] UNHCR, 2010 Global Trends (2011). United Nations High Commissioner for Refugees. Retrieved April 2, 2012 http://www.unhcr.org/4dfa11499.html

# Appendix

Table 19: Are IDPs different? Ages 6-11

| Variable: | Education Accumulation Model | | | School Enrollment Model | | |
|---|---|---|---|---|---|---|
| | All Migrants (1) | Migrants Conf (> 0.3) (2) | All obs with Conf (> 0.3 ) (3) | All Migrants (4) | Migrants Conf (> 0.3) (5) | All with Conf (> 0.3 ) (6) |
| IDP | -0.095** | -0.084 | -0.105** | -0.014* | -0.024** | -0.008 |
| | (0.04) | (0.06) | (0.04) | (0.01) | (0.01) | (0.01) |
| Sex | -0.105*** | -0.145*** | -0.166*** | -0.009*** | -0.008* | -0.010*** |
| | (0.01) | (0.03) | (0.02) | (0.00) | (0.00) | (0.00) |
| Conflict | -0.048 | 0.084 | -0.023 | -0.006 | -0.001 | -0.032*** |
| | (0.04) | (0.06) | (0.04) | (0.01) | (0.01) | (0.01) |
| Capacity | 0.144*** | 0.252*** | 0.286*** | 0.002 | 0.002 | 0.022** |
| | (0.05) | (0.08) | (0.05) | (0.01) | (0.01) | (0.01) |
| Urban | -0.020 | -0.016 | 0.009 | 0.009*** | 0.014*** | 0.023*** |
| | (0.02) | (0.03) | (0.02) | (0.00) | (0.00) | (0.00) |
| Mom yrs of sch. | 0.041*** | 0.039*** | 0.049*** | 0.004*** | 0.005*** | 0.007*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Dad yrs of sch. | 0.018*** | 0.027*** | 0.021*** | 0.003*** | 0.003*** | 0.003*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| N | 59811 | 18975 | 57815 | 59809 | 19000 | 57893 |
| F | 712.62 | 252.27 | | | | |
| $P(F) > 0$ | 0.000 | 0.000 | | | | |
| $R^2$ | 0.692 | 0.6743 | 0.6469 | | | |
| $\chi^2$ | | | | 1628.8 | 737.16 | 2541.03 |
| $P > \chi^2$ | | | | 0.000 | 0.000 | 0.000 |
| Pseudo $R^2$ | | | | 0.143 | 0.136 | 0.173 |

Note: Also controlled for age, race, family size, disability, employment status of father, automobile ownership, wall type, computer ownership, class of father's work, class of mother's work, mother's number of children, and department.
Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: Selection implies restricting the sample to subgroup which contains all IDPs and migrants leaving in region with high conflict.

Table 20: Are IDPs different? Ages 12-17

| Variable: | Education Accumulation Model | | | School Enrollment Model | | |
|---|---|---|---|---|---|---|
| | All Migrants (1) | Migrants Conf (> 0.3) (2) | All obs with Conf (> 0.3 ) (3) | All Migrants (4) | Migrants Conf (> 0.3) (5) | All with Conf (> 0.3 ) (6) |
| IDP | -0.412*** | -0.440*** | -0.443*** | -0.051*** | -0.101*** | -0.057*** |
| | (0.09) | (0.13) | (0.09) | (0.02) | (0.03) | (0.02) |
| Sex | -0.462*** | -0.478*** | -0.506*** | -0.037*** | -0.039*** | -0.050*** |
| | (0.03) | (0.05) | (0.03) | (0.01) | (0.01) | (0.01) |
| Conflict | -0.066 | 0.056 | -0.131* | -0.016 | 0.004 | -0.019 |
| | (0.08) | (0.12) | (0.07) | (0.01) | (0.02) | (0.01) |
| Capacity | -0.159 | -0.002 | -0.054 | -0.023 | -0.012 | -0.016 |
| | (0.10) | (0.15) | (0.09) | (0.02) | (0.03) | (0.02) |
| Urban | 0.365*** | 0.429*** | 0.502*** | 0.051*** | 0.069*** | 0.076*** |
| | (0.03) | (0.06) | (0.04) | (0.00) | (0.01) | (0.01) |
| Mom yrs of sch. | 0.099*** | 0.103*** | 0.114*** | 0.010*** | 0.009*** | 0.010*** |
| | (0.00) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) |
| Dad yrs of sch. | 0.052*** | 0.059*** | 0.062*** | 0.008*** | 0.007*** | 0.008*** |
| | (0.00) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) |
| N | 48387 | 15512 | 48960 | 48438 | 15540 | 49048 |
| F | 287.77 | 114.54 | | | | |
| $P(F) > 0$ | 0.000 | 0.000 | | | | |
| $R^2$ | 0.482 | 0.478 | 0.476 | | | |
| $P > \chi^2$ | | | | 0.000 | 0.000 | 0.000 |
| Pseudo $R^2$ | | | | 0.190 | 0.192 | 0.190 |

Note: Also controlled for age, race, family size, disability, employment status of father, automobile ownership, wall type, computer ownership, class of father's work, class of mother's work, mother's number of children, and department.
Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 21: Humanitarian Situation Risk Index: Conflict Index

| Variable Name | Description |
|---|---|
| Subversive Actions Rate | Hostile acts by subversive groups per 10,000 inhabitants, against police or civilian infrastructure. Includes attacks on police installation, attacks on planes, urban attacks, armed contact, ambushes and sieges. |
| Unilateral Attacks | Total number of incursion with no combat |
| Total Confrontations | Total confrontations between Public Forces and subversive groups |
| Total Deaths | Total deaths in combat |
| Mine incident rate | Number of mine incidents per 10,000 inhabitants |
| Homicide rate | Homicides per 10,000 inhabitants. Common homicides include all deaths by weapon with the exception of traffic-related homicides |
| Council member homicide rate | Homicide rate among council members, per 10,000 inhabitants |
| Union member homicide rate | Homicide rate among union members, per 10,000 inhabitants |
| Teacher homicide rate | Homicide rate among teachers, per 10,000 inhabitants |
| Indigenous homicide rate | Homicide rate among indigenous people, per 10,000 inhabitants |
| Massacre victim rate | Number of deaths in massacre per 10,000 inhabitants. A collective homicide or massacre is committed when the total killed are four or more persons. It must be committed at the same place, same time, by the same authors, and against persons unable to defend themselves |
| Kidnap victim rate | Kidnap victims per 10,000 inhabitants, including both simple and extorsive kidnap victims. A kidnapping is the retention or hiding of a person in order to exchange their freedom for some resource, avoid some act, or for a publicity of political end. |
| FARC Groups | Number of FARC groups present |
| ELN Groups | Number of ELN groups present |
| Expulsion displacement rate | Rate of forced displacement per 10,000, where the person is forcibly expelled from the municipality |
| Reception displacement rate | Rate of forced displacement per 10,000, where the person is forcibly expelled to the municipality |

Table 22: Humanitarian Situation Risk Index: Response Capacity Index

| Variable Name | Description |
|---|---|
| Teachers with higher education | Number of teachers with higher education |
| Student:teacher ratio | Total number of students by number of teachers |
| Middle education institutional presence | Number of middle education institutions per 10,000 inhabitants |
| SENA continuing education center presence | Number of SENA institutions per 10,000 inhabitants |
| ICBF Family Welfare Institute rate | Binary value, present or not present |
| Health center presence | Number of health centers per 10,000 inhabitants |
| Vaccination coverage | Percentage of population covered by vaccinations |
| Compensation services presence | Rate of compensation services present per 10,000 inhabitants |
| Judicial dispatch presence | Rate of presence of judicial dispatches per 10,000 inhabitants |
| Conciliation center presence | Rate of presence of conciliation centers per 10,000 inhabitants |
| Police station presence | Binary value, present or not present |
| Rural citizen soldier presence | Binary value, present or not present |
| Presence of major highway | Binary value, present or not present |